A Review and inventory of fixed installation Passive Acoustic Monitoring methods and technologies (revised with appendix 26 May 2010)

Prepared by Bio-Waves Inc

E&P SOUND & MARINE LIFE PROGRAMME

www.soundandmarinelife.org

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From: Tom Norris [thomas.f.norris@cox.net]
Sent: 27 May 2010 21:55
To: David Hedgeland; 'Campbell, John'
Cc: oswald.jn@gmail.com; sousalima.renata@gmail.com
Subject: RE: Dissemination of reports
Attachments: Norris et al JIP Fixed PAM Review (revised with appendix 26 May 2010).pdf

Dear John and David:

Please find attached the revised version of our report to the JIP: 'A Review and Inventory of Fixed Installation Passive Acoustic Monitoring
Methods and Technologies'. As per your request, Julie Oswald has added an appendix reviewing the localization capabilities of software packages that were included in her main review. Please be aware that this is not intended to be a comprehensive review of all software packages with localization capabilities, but rather just those software packages *that were already included* in her review of automated detection and classification methods as was agreed upon in our discussions on this topic with you. I hope this meets your needs. If not, please advise further.

Assuming the report is now acceptable as a final deliverable, I will be submitting our final invoice shortly.

I think you and the JIP members will be pleased to hear that we are in the process of submitting the report to Aquatic Mammals as a special edition of their journal, to be published (with editors approval of our reports) sometime this year. We are also planning to present posters on our chapters at the upcoming Acoustical Society of America/Pan American/Iberian meeting on Acoustics in Cancun Mexico.

I look forward to hearing any feedback (positive or negative) that you might have on the report so that we can continue to provide you with the highest quality service for future endeavors.

On behalf of my team,

Sincerely,
-Tom Norris

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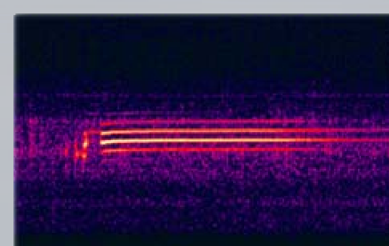
Tom/Julie

Please advise when updated (as discussed below) final version of the report will be available?

E&P Sound and
Marine Life Programme

A Review and Inventory of Fixed Installation Passive Acoustic Monitoring Methods and Technologies



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A Review and Inventory of Fixed Installation Passive Acoustic Monitoring Methods and Technologies:

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Executive Summary

Fixed Passive Acoustic Monitoring (fixed PAM) systems have the capability to monitor underwater sounds over a wide range of spatial and temporal scales. The Joint Oil & Gas Industry Programme on Sound and Marine Life (JIP) is in need of information on cost-effective ways to collect data for assessing marine mammal distribution, abundance, movements, behaviors, and habitat use in relation to offshore oil and gas exploration and production (E&P) activities. Our team was tasked by the JIP to provide an inventory and review of fixed PAM technologies for monitoring marine mammals in relation to E&P activities. In this report, we review three main types of fixed PAM systems: 1) Autonomous recorders (ARs), 2) Fixed, cabled hydrophones (FCHs), 3) Radio-linked hydrophones (RLHs), and 4) computer-based methods for automated detection, extraction, and classification of marine mammal sounds.

Our general approach consisted of researching and compiling primary information from peer-reviewed (i.e., published) scientific literature, with additional information sources such as grey and white literature, abstracts, conference presentations, press releases, product brochures, equipment manuals and websites used when necessary. Online search engines and extensive electronic bibliographic and journal databases from Cornell University, the University of California, San Diego, and The University of Hawaii were used. In some cases PAM developers and users were contacted directly to provide further details on their systems. Finally, public requests for information were posted to Bioacoustics-L and MARMAM list-serves. A bibliography of relevant references and reprints was compiled online using EndNoteWeb library.

We defined a fixed autonomous acoustic recording device (AR) as any electronic recording system that acquires and stores acoustic data internally (i.e., without cable or radio links to a receiving station), is deployed semi-permanently underwater (e.g., via a mooring, surface buoy, or resting on the sea-floor), and must be retrieved after the deployment period to access the data. We reviewed over 30 types of ARs that can be used for recording marine mammal sounds. These vary greatly in price, ease of deployment, and capabilities. They range from small hand-deployable units for detecting dolphin and porpoise clicks in shallow waters, to large units that must be deployed from a large research vessel in deep water and record continuously for several months to a year that have been used to detect a variety of species.

Fixed cabled hydrophone systems (FCHs) are typically permanently or semi-permanently located on the seafloor. They have the capability to be powered continuously by an external source and can send data continuously to a receiving station that is usually located on shore. Examples include the U.S. Navy's low-frequency Sound Surveillance System (SOSUS) and underwater test ranges outfitted with seafloor hydrophone arrays (e.g., AUTEC in the Bahamas). Also included in this review are large scale ocean observatories, 'hydrophone networks', deepwater neutrino observatories, and fixed hydrophone systems designed for marine mammal research.

Radio-linked hydrophone (RLH) systems consist of one or more hydrophones that are moored or fixed to the seafloor. These systems can transmit acoustic signals via radio-waves to a receiving station on shore which allows acoustic data to be remotely monitored and processed in real, or near real-time. Examples of RLHs include customized systems that have been developed to monitor large baleen whales in the shipping lanes off Boston Harbor, Massachusetts, and in heavily trafficked waterways in the St. Lawrence Marine Park, Saguenay River, Quebec. Some examples of RLH systems designed for other purposes that have been used to monitor marine mammals include the Comprehensive Test Ban Treaty Organization's International Monitoring System (CTBTO/IMS) which consists of satellite linked 'hydroacoustic stations' that were designed for worldwide monitoring of nuclear tests.

Autonomous recorders, fixed cabled hydrophones, and radio-linked hydrophone systems, each have their own advantages and disadvantages. In general, setup and infrastructure costs are highest for FCHs and RLHs and lowest for ARs. However, acoustic data bandwidth and collection capabilities, longevity of monitoring, and real-time capabilities are greatest for FCHs. Due to their autonomous nature and portability, AR systems are more flexible in their spatial configuration possibilities and potential locations of deployment. However, ARs require retrieval of the instrument for access to the data. Therefore, real-time monitoring of acoustic data is not possible using ARs. Because they use radio-based transmission networks, RLHs have real-time data acquisition capability, but usually are more limited in bandwidth and data transfer rates than FCH systems. RLH systems typically have lower installation and infrastructure costs than FCH's, but their development and maintenance costs can be higher. RLHs are usually located relatively close to shore and require a land-based receiving station, however, data can be processed in real-time, or pre-processed at the data-collection buoy. Hybrid systems that combine elements of ARs, RLHs and FCHs can provide a good compromise of cost and capability, by providing real-time (or near real-time) data acquisition and processing with the flexibility in deployment possibilities of ARs.

All of the fixed hydrophone systems and devices reviewed have the capability to generate enormous volumes of data which can be costly and time-consuming to review and analyze. Therefore, it is usually desirable to detect and classify marine mammal vocalizations contained in these datasets using automated or semi-automated methods. This process involves three main steps: 1) the detection of a potential sound of interest, 2) the extraction of relevant features from potential sounds of interest, and 3) classification of these sounds (based on the extracted features) as to a particular marine mammal species or species group. We review computer-based methods and readily-available software that can be used to accomplish these tasks. We identify the gaps in our capabilities and knowledge, and suggest ways forward to fill these gaps.

There are several software packages available for detection or classification. However, few perform both these tasks effectively and none are able to concurrently classify the vocalizations of a large number of marine mammal species with good accuracy. Methods for the detection and classification of many of the stereotyped sounds produced by baleen whales are relatively well developed. Automated methods that can handle variable acoustic signals, such as odontocete whistles, pulsed sounds (e.g., echolocation clicks), and non-stereotyped sounds produced by baleen whales are less developed. Of the methods reviewed here, the wavelet transform is an example of a method that has potential for the detection of all of these types of signals. Tree based models, Gaussian Mixture models, Hidden Markov models and artificial neural networks are among several other methods that are promising for use in signal classification tasks. However, these methods need to be tested and validated further, using sounds from a larger number of species.

Because of the great variability in the structure of marine mammal sounds, no single method is likely to be effective for automatic detection and classification of sounds from all species and populations. The development of effective, efficient, and standardized detection/classification methods for many species will require large, validated data-sets. The acquisition, maintenance and availability of such data-sets will require concerted and organized collaborative efforts. Comparative testing of different methods will require that portions of these large databases contain detailed annotations of validated marine mammal sounds as well as annotations of confounding, non-marine mammal sounds (such as machinery and other man-made noise). Providing access to common datasets and convening workshops that focus on furthering detection/classification methods are two effective ways to address these important issues in automated detection and classification of marine mammal sounds.

In summary, this report in includes a review of three main types of fixed PAM systems and the detection/classification algorithms that can be used to efficiently process the large volumes of data collected from these systems. Important aspects to consider when selecting which device or system and analysis methods to use include the target species of marine mammals, longevity of monitoring, area to be monitored, the bandwidth and other characteristics of sounds to be monitored. Other important issues to consider include the need for real-time processing and availability of the data, versus post-processing and archival availability of acoustic data. In addition, ambient noise, including biological noise, and noise produced by oil and gas exploration activities, all affect the performance of PAM systems. Therefore, noise conditions and their effects on each of these PAM systems should always be considered when selecting any PAM technology. Each of these factors should be evaluated when deciding which type of technology is best suited for the project requirements, goals and questions to be answered.

Finally, it is essential to consider the biology of the target species (or species groups) that are being monitored or studied using fixed PAM technology. This relates to all aspects of the decisions made when choosing the type of fixed PAM monitoring system to be used. A carefully chosen monitoring system and well designed plan (or study) will incorporate both fixed PAM technologies and automated processing methods that can efficiently process acoustic data. With these considerations in mind, the acoustic data collected by fixed PAM systems can provide useful and valuable information that is relevant to understanding biology and ecology of the target species and, and the effects, if any, of anthropogenic noise on marine mammals.

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A Review and Inventory of Fixed Autonomous Recorders for Passive Acoustic Monitoring of Marine Mammals

Renata S. Sousa-Lima, Thomas F. Norris, & Julie N. Oswald

Abstract

Fixed autonomous acoustic recording devices (autonomous recorders) are reviewed. These are defined as any electronic recording system that acquires and stores acoustic data internally (i.e., without cable or radio links to a fixed platform or receiving station), is deployed semi-permanently underwater (via a mooring, buoy or attached to the sea-floor), and must be retrieved after the deployment period to access the data. More than 30 autonomous recorders currently are available for recording marine mammal sounds. These vary greatly in capabilities and costs, from small hand-deployable units for detecting dolphin and porpoise clicks in shallow water to larger units that can be deployed in deep water and can record at high frequency bandwidths for over a year, but must be deployed from a large research vessel. Capabilities and limitations of the systems reviewed here are discussed in terms of their applicability to study marine mammals, and for monitoring and mitigation in relation to oil and gas production and exploration activities.

Key words: passive acoustic monitoring, autonomous recorders, fixed systems, marine mammals, acoustic monitoring, mitigation

1 Introduction

Marine mammals live most of their lives out of view of humans under the ocean surface. The difficulties inherent in studying the effects of human activities on these animals can be overcome only through the application of technology (Samuels & Tyack, 1999). Most species of marine mammals are acoustic specialists that rely on sounds for communication and navigational purposes. Scientists and engineers have developed passive acoustic based technologies that use the sounds produced by marine mammals to more effectively study them.

In 1880, Pierre Curie and his brother found that when mechanical pressure was exerted on a quartz crystal, an electric potential is produced. This finding has since enabled advances in passive acoustic monitoring (PAM) technology that made it possible for researchers to listen, record, store, and analyze marine mammal sounds. In the recent past, limitations in the technologies and methods available, as well as high costs, have inhibited the development and application of passive acoustics for marine mammal monitoring. In addition, technical expertise that was typically beyond that of most field biologists has been needed for PAM operations (e.g., acoustic monitoring from a ship or through cabled and radio-linked PAM systems). The development of autonomous underwater sound recorders (ARs) has greatly reduced the costs and expertise required to monitor marine mammal sounds for extended time periods. Today, ARs can be easily deployed on the bottom of the ocean to record acoustic data for days, weeks or months at a time. The ARs can then be retrieved and the data can be downloaded for post-processing and analysis by technicians or biologists. This approach allows ARs to be deployed and retrieved by field personnel with only a limited amount of training or expertise and frees up valuable time, resources and funding, which can then be applied to data processing and analysis.

ARs are most cost effective when used in extreme or remote locations where access is limited or difficult, such as polar regions and deep-sea areas where travel distances are great or conditions are too harsh to conduct surveys aboard research vessels. They are also useful for detecting marine mammals in areas where the occurrence of these animals is infrequent, or where ship-based surveys would have a very high cost per detection (Mellinger & Barlow, 2003). The cost savings in the use of ARs is achieved due to their autonomous nature, i.e., their operation is independent of the presence of an operator. The disadvantage is that these instruments must be recovered to access the data recorded, which can only then be analyzed. The pros and cons of post-processing and real-time data processing need to be evaluated carefully for each application, and will be discussed in greater detail later in this review. If archival data is useful, such as during acoustic prospecting efforts (i.e., during pilot studies), ARs should be considered as a cost-effective approach. In general, setup and infrastructure costs are highest for other types of PAM systems (fixed cabled hydrophones, towed hydrophone arrays, and real-time radio- or satellite-linked hydrophones) and lowest for ARs. However, acoustic data bandwidth and collection capabilities are usually higher for these other types of PAM systems. AR systems are more flexible in their configuration, timing and location of deployment, and are less obtrusive to both animals (e.g. arrays towed by vessels that may interfere with marine mammal behavior) and to vessel traffic when deployed on the ocean floor without a surface buoy.

For the purpose of this review, we define a fixed autonomous acoustic recording device as: *Any electronic recording device or system that acquires and stores acoustic data internally* (i.e., without cable or radio links to a fixed platform or receiving station), *is deployed semi-permanently underwater (usually via a mooring, buoy or attached to the sea-floor), and must be retrieved after the deployment period to access the data.*

We provide a critical view of the state-of-the-art of AR technology including both 'traditional' autonomous recording devices (i.e. those designed specifically for recording geo-physical events, underwater noise, and marine animal sounds), as well as 'non-traditional' recording devices (e.g., electronic animal tags such as acoustic data-loggers).

We review the history of AR development, their capabilities and constraints with respect to different application requirements (monitoring versus mitigation), specific environments they can be used in, and perhaps most importantly, the species to be monitored and the biological questions that are to be addressed. We also discuss AR capabilities and constraints with respect to their use in monitoring marine mammals in relation to oil and gas exploration and production activities.

Historical Overview of the Development of Autonomous Recorders

During the late 1960s, a change in spatial scale occurred in marine geophysical research when researchers focused their studies on earthquakes in smaller areas of the seafloor. This shift required higher accuracy and more precise geophysical instruments and led to the development of 'autonomous instruments' for monitoring earthquakes underwater. These fixed autonomous instruments, called *Ocean Bottom Seismometers* (OBSs), were able to measure small movements of the Earth's crust (Loncarevic, 1977). An OBS is designed to rest on the ocean floor and uses a sensor called "seismometer" to make measurements. The seismometer sensor is comprised of a heavy mass suspended on a spring between two magnets. Seismometers use the principle of inertia: the resistance of an object to a change in its state of motion. When the earth's crust shifts, the seismometer and its magnets move concurrently, but the heavy mass momentarily remains in its original position. The relative movements of the mass through the magnetic field produce electrical currents which are then measured by instrumentation in the OBS (Dorman, 2001; Ocean Instruments, n.d.).

A typical OBS consists of a seismometer, a data logger, batteries to power the device, weight to sink it to the sea floor, a remotely-activated (or timed) release mechanism, and flotation to buoy the instrument back to the surface (Dorman, 2001; Ocean Instruments, n.d.). By 1975, the OBS became an operational tool used by a dozen or so research groups in at least seven countries (Loncarevic, 1977). Since then, OBSs developed by researchers from France, Japan, Australia, Germany, Russia and the U.S. have been used extensively in geophysical research efforts.

The ground motion caused by earthquakes can be extremely small (e.g., less than a millimeter) or quite large (e.g., several meters). Small motions have relatively higher frequencies, so monitoring them requires special short-period OBSs that can record motions up to hundreds of times per second (Ocean Instruments, n.d.). These high frequency OBSs that typically record up to 100 Hz are also capable of recording low frequency sounds produced by large baleen whales (blue and fin whale sounds have frequencies below 100 Hz). McDonald et al. (1995) were the first to use OBS data to study marine mammals in a study in which blue and fin whale calls were detected and localized in deep waters during a seismic study on the southern Juan de Fuca Ridge off the coast of Oregon. These data were recorded incidentally during a seismology experiment (McDonald et al., 1995).

A similar device called an *Ocean Bottom Hydrophone* (OBH) is also used by geologists to study seismic activity in the ocean. An OBH has a hydrophone instead of (or in addition to) a seismometer. Experiments using both vertical seismometers and hydrophones have shown a higher signal-to-noise ratio for large whale low-frequency calls on seismometers than on hydrophones (McDonald et al., 1995), even though hydrophones are able to record higher frequencies than seismometers. Besides John Hildebrand's group at Scripps Institution of Oceanography Whale Acoustics Lab (McDonald et al., 1995), Christopher Fox, at the National Oceanic and Atmospheric Administration's (NOAA) Pacific Marine Environmental Laboratory (PMEL), also used OBSs/OBHs to gather marine mammal data since the early 1990's (e.g., Stafford et al. 1999; C. W. Clark, personal communication, November 28, 2009).

OBSs and OBHs were too expensive for most researchers to purchase in quantities needed to study marine mammals, so during the 1990s, several laboratories started to develop their own ARs in an attempt to lower the costs and to modify the design for their own needs. One example was a relatively small experimental instrument with a single hydrophone that was developed by John Orcutt at Scripps Institution of Oceanography (SIO). The low-cost and smaller size of the Low-Cost Hardware for Earth Applications & Physical Oceanography (LCHEAPO, Figure 1) was the direct result of the availability of new, low-power consumer electronics. Different institutions were then collaborating in the deployment and testing of these instruments (C. W. Clark, personal communication, November 28, 2009). An example was the collaboration between Peter Worcester's group at SIO and Cornell University during the monitoring of the ATOC transmissions on the Pioneer Seamount during humpback whale research off Hawai'i (Frankel & Clark, 1998), and during research on blue and fin whales off Southern California (Clark & Fristrup, 1997; Fristrup & Clark, 1997).

Soon thereafter, John Hildebrand (Scripps Institution of Oceanography Whale Acoustics Lab), Christopher W. Clark (Bioacoustics Research Program at Cornell University - BRP), and Haru Matsumoto (National Oceanic and Atmospheric Administration's Pacific Marine Environmental Laboratory – NOAA/PMEL) were among the first to develop and deploy their own ARs designed specifically to collect bio-acoustic data from marine mammals. Thus began the cultural transmission of oceanography to bio-acoustics, as some of these instruments (such as the pop-ups from Cornell University), were the direct result of researchers and engineers from these two expertise areas, and from two different institutions (SIO and BRP) exchanging technology and knowledge to help the initial design of that instrument (C. W. Clark, personal communication, November 28, 2009).

More recently, advances in low-power electronics, high-data capacity data-storage, computer processing technology, and power supply units have enabled the development and use of ARs capable of monitoring the acoustic environment and behavior of many species of marine mammals. Improvements in electronic data-storage and battery technologies have allowed data collection for much longer periods of time and at higher data-sampling rates than previously possible. These ARs will be reviewed below with examples provided of their use in marine mammal research and monitoring.

2 Methods

We conducted an inventory of autonomous recorders by searching commercially available systems online using the beta version of Scientific WebPlus (ISI Web of Knowledge), a web-based search engine that is focused on scientific web content, recent scientific developments other science based information selected by Thomson Reuters editors. A search for the string "autonomous underwater sound recording" resulted in 149 hits of websites. We looked at each hit for relevant information and assumed that if the item was commercially available it would be available on the internet. We also searched www.oceanbusiness.com database, which summarizes a list of companies around the world that do business related to ocean resources.

Additional information included in scientific papers and reports was searched using the Google search engine (both the regular web-search and Google scholar) as well as all relevant library databases available from Cornell University and the University of Hawaii. A request for information was sent to Bioacoustics_L and MARMAM listservers, which are commonly viewed by marine mammal researchers and bio-acousticians and other professionals working on passive acoustic monitoring of marine mammals. Conference proceedings and abstracts (e.g. the Acoustical Society of America) were also reviewed for relevant information. Finally, researchers, organizations and companies were contacted directly via e-mail to inquire about specific systems or devices. The resulting bibliography was compiled on an EndnoteWeb library.

3 Results

3.1 Inventory of Current Fixed Autonomous Recorders

We found over 30 instruments that fit the working definition of fixed autonomous acoustic recording devices used for marine mammal monitoring (Table 1). These included miniaturized recording devices (i.e. data-logger animal tags) that have been modified or can be implemented as fixed ARs (Au et al., 2000; Arias et al., 2008; Akamatsu et al., 2008; Thode et al., 2006).

The instruments reviewed here were in various stages of development. Some AR systems that were researched were in early stages of development and did not have detailed specifications available, and in some cases we did not receive a response to our direct attempts at contacting developers for further information (e.g., the *Digital Hydrophone* from MarSensing Lda. in Portugal, and the *Autonomous Acoustic Recording System* developed by Ming-Hao et al,. 2007), so we were unable to provide complete or any information on some of these systems.

Instruments researched that have very limited application on passive acoustic monitoring were also not included in the inventory. An example is the system designed by Hayes et al. (2000): an "inexpensive animal recording and tracking system" (see also Møhl et al., 2001 for a similar passive location system). The system designed by Hayes et al. (2000) used autonomous sound-recording buoys deployed at several locations simultaneously to produce a sparse hydrophone array. Each buoy is an instrument that contains a global positioning system (GPS) location logger, a portable stereo digital audio tape (DAT) recorder with a hydrophone connected to one channel, and a VHF radio signal for time synchronization connected to the second channel. The authors point out that the main disadvantage of the system for PAM applications is the duration of the recordings. DAT tape recorders are capable of recording sounds for a maximum of 6 hours (using a 90-m tape and setting the recorder to "long-play" mode of 32 kHz), which is not enough for most PAM applications. Note that the µRUDAR™ (Cetacean Research Technology, 2010, Figure 2), although also limited in recording duration (10 hours), uses a compact flash card as storage media which, along with hard-drives, have mostly replaced DATs in portable recording devices. Therefore, Hayes et al.'s instrument is now considered outdated and is not further reviewed or included in Tables 1 and 2 but the µRUDAR™ is. In a number of cases, newer versions of the instruments included in this inventory are also being developed and are noted as such in Table 2.

3.2 Capabilities of Fixed Autonomous Recorders

ARs provide a cost-effective way to determine the presence, relative numbers and distribution of vocalizing marine mammals in space and time. The capabilities of the ARs that are necessary for monitoring marine mammals will vary according to the goals and biological questions, the sound production behavior of the specie(s) of interest, the environment in which they are to be deployed, and the ambient noise characteristics. For example, monitoring the seasonal occurrence of baleen whales usually requires deployments of several months to a year. However, because baleen whales produce low frequency sounds with good propagation characteristics, the requirements for spatial coverage and sample rates are relatively low (usually less than 1 kHz; Wiggins, 2003) compared to those that would be required to monitor most species of odontocetes over a similar area. Low sample rates required to record low-frequency sounds also allow modest power and storage capabilities for the AR.

In general, odontocetes produce mid- (whistles around 20 kHz) to high-frequency sounds (pulsed clicks upwards of 20 kHz) that do not propagate as well as sounds produced by baleen whales (usually below 1 kHz). This is because higher frequencies attenuate rapidly and the pulsed signals produced by odontocetes often have very narrow beam patterns. Because of these acoustic characteristics, odontocete signals are likely to be missed if the sensors are not located close to the beam axis (e.g. harbor porpoises - *Phocoena phocoena*; Kyhn et al., 2008). As a result, the spatial scales at which odontocetes can be monitored are smaller as compared to baleen whales. Therefore, the coverage of a given area with AR sensors to monitor odontocete echolocation clicks (pulsed sounds) must be relatively dense (i.e. more sensors per unit of area). Monitoring other odontocete sounds, such as whistles, might not require such densely populated sensor arrays but do need to be sampled at higher sampling rates than the lower frequency sounds produced by baleen whales. Finally, the higher sample rates required to record odontocete sounds require greater storage and power supply capabilities.

So how should a user choose an AR system? First, the question and goals to be addressed must be clearly defined and considered. This will in turn dictate the requirements of the AR system. Based on the costs, capabilities and specifications of AR system, and deployment and retrieval issues related to the monitored area, the user then may consider the options available. For example, suppose the scientific question of interest concerns the effects of oil and gas exploration and production activities on the spatial distribution of singing humpback whales (*Megaptera novaeangliae*) on their breeding grounds during winter-time when animals are singing for many hours continuously. Addressing this question will require multiple time-synchronized ARs that can be deployed close enough to each other so that each AR can record the same sounds for multiple whales to allow localization and tracking of multiple animals for 3-7 months, sampling at relatively low frequencies (1-2 kHz). If sampling schemes are available (i.e., recordings made at pre-defined intervals), the AR can be programmed to record on a duty cycle of 30 minutes on, 30 minutes off, for example (suppose analysis time is a constraint). This will save on power, storage, and post-processing requirements. The minimum number of units required and their deployment geometry are related to the sound propagation profile of the area. The farther sound travels, the fewer the number of AR units that are needed to cover the area (the maximum number of units is usually limited by budget). Humpback whale breeding grounds are typically shallow (< 100 m), therefore the depth rating requirement of the AR is relatively modest. Other issues, such as high fishing activity or the presence of pirates in the area, the type and availability of deployment/retrieval vessels, and the amount of funding available, will all affect the best choice for an AR device.

Choosing an AR system may not be as simple as this example in practice. If the question was "What is the relative occurrence of odontocetes in an area?", high sampling frequencies would be required which in turn would limit deployment duration. To provide long-term continuous acoustic records of odontocete calls using an autonomous instrument, there are three main requirements for the data acquisition electronics: low-power, high-speed digitization, and high-capacity data storage. As with any battery-powered autonomous instrument, low-power components are essential for long duration deployments. High-speed digitization is necessary to record broad-band odontocete calls and to provide enough bandwidth to record the entire range of the signal for call identification (Oswald et al., 2004). High-speed digitization coupled with long duration recordings requires a high-capacity data storage capability (Wiggins & Hildebrand, 2007). In most cases this is achieved using multiple hard or flash drives which require a micro-controller and firmware dedicated to controlling the data-recording process (e.g., HARPs, Wiggins & Hildebrand, 2007). These tradeoffs in capability are important to understand when choosing the best AR available for a particular application. The next section will explicitly discuss some of the most important tradeoffs in choosing an AR system.

3.3 Tradeoffs among Fixed Autonomous Recorder Capabilities and Limitations

ARs have self-contained power supplies and data acquisition and storage electronics which constrain the design and capabilities of these systems due to tradeoffs between power supply, data storage capacity, sampling frequency, and instrument size and depth rating (which will in turn affect costs and deployment duration). Each AR developer has found a different solution to manage size, cost, and system capabilities tradeoffs. System tradeoffs are critical issues in the choice of an AR system for application during oil & gas exploration and production activities or any PAM study. The main limitations on the duration of deployment are sampling frequency and battery capacity. Increased power requirements have a direct effect on the number of batteries included in the package, therefore increasing both the size of the instrument and the flotation requirement. The size of the instrument package will determine the costs of deployment and retrieval.

Figures 3 and 4 illustrate the tradeoffs of the AR capabilities and how these influence each other. For example, when going from less to more power, one can increase the sampling frequency to record higher frequency sounds, both of which will require higher data storage capacity at the expense of deployment and recording duration. Also, more batteries to power the instrument mean a bigger package that might in turn increase the costs of instrument deployment and retrieval. The more hydrophones on a unit, the greater the data storage requirement which will impact deployment duration, and increase the amount of batteries needed. Systems that can be deployed at greater depths are usually more expensive due to special housings, so as the size and complexity of the system are increased, budgetary demands also generally increase.

Instruments like the HARP (see Table 2 and Figures 5 and 6; Wiggins & Hildebrand, 2007) can provide high sampling rates but limited deployment durations. The HARP has 1.92 TB of storage capacity. This will provide for approximately 55 days of continuous sampling at 200 kHz or about one year continuously at a lower sample rate of 30 kHz. The HARP package can be quite large because of the battery and storage requirements, as well as the depth rating of 7,000 m (requiring a high pressure capable housing, see Table 2). Note that the HARP package has been reduced in size for other applications such as deployments from small boats and on gliders. To deploy large HARPs, a relatively large (> 80 ft) oceanographic ship or mid-sized fishing vessel with a winch and an A-frame (Figure 5) is required, deployment and retrieval costs which need to be considered when planning for their use.

Proportionately, the components that use the greatest amount of system power are the hard disk drive and hard drive controller (e.g., on HARPs). The data acquisition rate is indirectly related to power consumption because it determines how frequently the hard disk will need to be accessed and written to. For example, in Cornell BRP's pop up (or MARU, Figure 7, Table 3), the digital acoustic data are temporarily saved to a buffer which, once filled up, downloads the data to the hard drive. Data recorded at a sampling frequency of 2 kHz would fill up this buffer every three minutes, requiring access to the hard drives and therefore consuming power each time data are saved. The hard drive runs for six seconds every three minutes when data writing is occurring. The standard battery pack will keep the recording running continuously for a little over 100 days. At twice the sample rate (4 kHz) the data storage buffer will fill every 1.5 minutes and the drive will have to run twice as often as at the 2 kHz rate – dropping the standard battery life to 50 days. At 6 kHz the buffer will fill every 45 seconds and the efficiency of shutting down the hard drive between data writing sessions is lost so that it runs continuously to record the data flow – dropping the battery life to about 22 days. At 10 kHz the battery life drops to 20-22 days. At 20 kHz the battery life drops to 18-20 days, and so on.

Hard drive space becomes a limiting factor in pop-ups at sample rates greater than 20 kHz (see Table 3). The standard hard drive stores 80 GB of data. Therefore, at high sampling rates, data storage capacity, as opposed to power supply, can limit AR monitoring duration. Another example is the HARP, which is able to sample at 200 kHz and has a much higher storage capacity (1.92 TB) than pop-ups. The standard HARP power configuration (estimated at 330 Amp-hours using 192 D size alkaline batteries) recording continuously at the maximum sample rate will fill up the hard disks before the battery capacity is reached (Wiggins & Hildebrand, 2007).

The type and size of the storage media also influence the tradeoffs among sampling frequency, deployment period, power supply and, consequently, costs (more batteries, bigger housing, larger instrument, higher deployment costs). Recently, solid state flash memory has dropped significantly in price, and increased in capacity, offering an alternative to hard drives which are bigger, heavier, and consume more power. Hard drives are still used due to a greater storage capacity per unit and lower price than solid state flash memory cards (at this time, hard drives have approximately ten times more storage capacity than flash cards). Nonetheless, due to their solid-state design (enables reduction in self-noise from moving parts) and lower power consumption, flash cards are rapidly replacing hard disks, especially as they drop in price and increase in total storage capacity.

3.4 Continuous recording vs. sampling schemes

When determining what type of sampling schemes to use, it is important to understand the acoustic behavior of the target species to be monitored. Perhaps more importantly, the goals and questions to be addressed using data collected from ARs, must be clearly defined. These factors will affect the types of sampling schemes that are appropriate for the task. For many preliminary or 'prospecting' PAM applications, continuous recording is desirable because complete information about the acoustic behavior of animals and their acoustic environment is often lacking. Initially, medium- to long-term acoustic prospecting must be first completed to determine what species are present, what types of sounds they produce, and how often they are produced. However, the amount of data generated by continuous recordings is so large that automatic detection or sampling schemes must often be applied to the data during post-processing and analysis. The tradeoff between minimizing the non-sampling period and maximizing the time periods during which data is collected must be considered in relation to the monitoring requirements and temporal aspects of the acoustic behavior for the species being monitored. For example, a sampling scheme of 12 hrs on and 12 hrs off for each day would not provide adequate data coverage to examine whether a diel calling pattern occurs in a particular species (Wiggins & Hildebrand, 2007). Alternatively, a sampling scheme of 5 minutes on and 5 minutes off would be adequate for examining this question and would also reduce power consumption, thus allowing longer monitoring durations.

Note that using a brief or very intermittent duty cycle for recording is not well suited for capturing acoustic signals and events that are very infrequent or random, but it is effective in documenting the pattern of occurrence of regularly occurring signals typical of some species. For example, humpback whales, which sing continuously for several hours at a time during the breeding season, have been monitored using the EAR at 3.3% duty cycle, or once every 15 min for 30 s (Lammers et al., 2008). Continuous acoustic recordings can be very useful for obtaining data for historical and geographical perspectives, or when researchers want to compare other phenomena present in the recordings through time (e.g., Northern right whale call characteristics; Parks et al., 2007) or space (e.g., humpback song comparisons across regions; Cerchio et al., 2001; Darling & Sousa-Lima, 2005).

Alternatively, triggering algorithms that will only record the sounds of interest or record any sound at preset time intervals, can be advantageous. This approach involves periodic sampling with the ability to turn "on" the recording device when signals of interest occur, which is also desirable from both a cost and a data management standpoint (Lammers et al., 2008). However, such sampling requires validation to ensure that signals of interest are not missed by the algorithms used and the vocal behavior and types of calls one is looking for must be well known.

Some systems (PAL, TPOD, CPOD, A-TAG, EAR, and AQUAclick; see Tables 1 and 2) have automatic call detection algorithms that trigger recording when predetermined call types are detected, or when some acoustic criteria are met. The PAL (Nystuen, 1998, 2006; Nystuen et al., 2007, Figure 8), the EAR (Lammers et al., 2008, Figure 9), and the DMON (Johnson, unpublished, Figure 10) pre-process the data based on knowledge of the sound of interest, saving storage space and consequently power. ‘Plug-in’ user-supplied automatic detection algorithms can also be used to automatically process, extract and store particular parts of the sounds of interest (DMON). Even more specific are the click detectors/loggers, such as the AQUAclick (includes a porpoise channel tuned to 130 kHz and a “dolphin” channel at 50 kHz, Figure 11), the T-POD and C-POD (Figures 12 and 13), and the A-TAG (Akamatsu et al., 2008), which do not record sounds but record information, such as time of occurrence of high-frequency odontocete clicks. Nevertheless, if the sounds of interest are too variable, which is the case for many marine mammal monitoring applications, this advantage is diminished.

Future HARP systems are planned to implement such triggering algorithms in the data loggers, resulting in much smaller quantities of recorded data (Wiggins & Hildebrand, 2007). While this approach seems reasonable, the drawback is that non-targeted calls and other sounds of potential interest would go unrecorded. For example, dolphin and pinniped sounds would not likely be recorded by an algorithm designed to detect low-frequency whale calls. Furthermore, investigating the structure and variability of ocean acoustic noise over various time periods would be difficult, if not impossible, using event-triggered acoustic data (Wiggins 2003).

Even when sampling schemes are used, ARs generate massive amounts of data that have to be reviewed and analyzed upon instrument retrieval. Methods for managing data processing for detection and classification of marine mammal sounds in the recordings will be needed to accomplish this efficiently.

Even though data compression schemes provide some means of decreasing power consumption rates and increasing deployment duration (Wiggins & Hildebrand, 2007), these approaches should be thoroughly tested so that recording fidelity is not compromised. New processors to analyze and pre-process data for some short time series recorders are being developed for some ARs such as the PALs (which use a variety different algorithms to identify sounds present, J. Nystuen, personal communication, November 15, 2008). Automatic detection and classification algorithms are an area of significant research and development and are reviewed elsewhere (Oswald et al. this report).

3.5 Capability of Collecting Non-Acoustic Oceanographic Data

Some ARs can have additional sensors to collect non-acoustic oceanographic data (see Table 2). The AMAR (Figure 14, JASCO, 2009a) collects data on water temperature and 3-axis orientation but can also include other sensors on request. A small, self-contained, external CTD data logger and/or sound velocity sensor are planned as new add-ons to the PANDA (see Tables 1 and 2, Figure 15). With the combined recordings of conductivity, temperature, pressure, sound velocity, and acoustic signals in a single integrated and compact system, PANDA will be very useful for shallow-water physical oceanographic studies (Koay et al., 2001). Sound speed data are important for accurately calculating sound time of arrivals when using multiple ARs to localize the source of the sound.

Miniaturized electronic devices (animal tags) can be used as sensors and data loggers in fixed ARs. Several types of electronic tags have been used in fixed ARs, for example, Thode et al. (2006) used slight modifications of an older version of the Acousonde (Figure 16, Burgess et al., 1998; Burgess, 2000) in designing the AAR (Tables 1 and 2, Figure 17). The Acousounde (Acousonde, n.d.), is a sound-recording animal tag with 2 acoustic channels that can sample up to 232 kHz and includes depth and internal temperature sensors and can have also 2-D acceleration/tilt sensors in the package. The A-TAG has been used to tag and study finless porpoises (Akamatsu et al*.,* 2008) and is yet another example of tag technology used in a fixed configuration (Wang et al. 2005).

The DTAG (Figure 18, Johnson & Tyack, 2003), a digital acoustic recording tag, contains an accelerometer, a magnetometer, and pressure sensors. It is designed to measure the tagged animal's orientation and depth at sampling rates of up to 50 Hz, much higher than traditional animal-tag time-depth recorders (Johnson & Tyack, 2003). The DMON is a fixed AR recently developed by the same group. The DMON is also capable of acquiring depth, temperature, and orientation data (Johnson, unpublished).

Tags provide the capability to record oceanographic data, animal orientation, and other information and have been used to study several aspects of the behavior of a variety of species.

Some examples include: northern elephant seals (OAR; Fletcher et al., 1996), humpback whales (CAP; Au et al*.,* 2000), beaked whales (DTAG; Arias et al. 2008), and sperm whales (UTDRT; Madsen et al., 2002), to name a few. The CritterCam (Marshall, 1998; Tables 1 and 2) is a relatively large animal tag that includes a miniaturized video and data recording device, stores time-stamped color video, hydrostatic pressure, water temperature, 3-axis accelerometer data, light level, water resistivity, battery level, compass direction, and other data. All of the tags listed above are able to collect sound data and could potentially be also used in a fixed AR configuration for PAM applications.

3.6 Internal Design of Autonomous Recorders

ARs typically include a robust pressure housing to protect the electronics, digital recording systems and batteries. An ideal AR requires high quality sensors, and low-noise electronics with a high-resolution digital recording system. AR internal design and external package configuration should be based on the specific questions and objectives the system is build to address.

3.6.1 Electronics

Each AR developer has come up with different solutions in designing their systems including more or less hardware to meet planned capabilities. Nonetheless, all systems basically include: a single or multiple hydrophones for sound acquisition; internal electronics to control the system and for acoustic data conditioning (e.g., signal amplifiers, anti-aliasing and band-pass filters, and analog-to-digital converters) and storage (hard drives, flash cards); and in some cases, electronics to allow the recovery of the device.

Pop-up developers designed their system with the objective of creating a compact device that could be deployed by a single person and at great depths. Therefore, a pop-up system includes additional recovery electronics to enable the retrieval of the instrument. The pop-up recovery system's electronics include an acoustic command recognition system, an audio signal communications system, a fail-safe time-release mechanism, a radio beacon, and a strobe light. The pop-up electronics are distributed on two plates that are housed within a borosilicate glass sphere. The sphere is place within a protective plastic helmet with the hydrophone and piezo speaker mounted externally on its side (Figure 19, BRP pop-up user's guide, unpublished).

The D-MON electronics configuration includes two circuit boards (Figure 10). The main board contains a digital signal processor, memory, power supply, and interface circuits. The sensor board contains sound acquisition circuits as well as depth and orientation sensors. This set of two boards can be used inside a pressure housing (e.g., a profiling float or a glider and requiring that the hydrophone(s) be wired to a penetrator) or it can also be used in a pressure-equalized housing (e.g., sealed in an oil-filled soft rubber sleeve) which can be deployed alone or in the wet space of an underwater vehicle (all of the sensors can be internal for protection and durability) (Johnson, unpublished).

High-capacity data storage is desirable for some applications (e.g., long-term continuous monitoring of species that emit high-frequency sounds). Such high-capacity data storage is achieved on AMARs and HARPs. The AMAR electronic board features 8 channels of 24-bit analog-to-digital conversion and can host up to 16 solid-state memory modules, each of which has a capacity of 128 GB, for a total of 2 TB of on-board memory (Figure 20). Similar high-capacity data storage on HARPs is achieved using 16 integrated laptop hard drives arranged in a block and addressed sequentially thorough a single 50-pin bus (Figure 21). The 16-drive block can be easily removed and replaced following instrument recovery (Wiggins & Hildebrand, 2007).

Monitoring high-frequency sounds of some marine mammal species can also be achieved by using triggering algorithms (as mentioned before). The PAL (Nystuen, 1998, 2006; Nystuen et al., 2007), the EAR (Lammers et al., 2008), and the DMON (Johnson, unpublished) are examples of ARs that include electronics to monitor continuous sound and only save information on sounds that trigger the detection algorithms. For example, the EAR has a signal conditioning module which includes circuitry that monitors the input signals for specific types of acoustic events (Lammers et al., 2008).

Other sensors, such as a compass (e.g., DASAR, Figure 22; Green et al., 2004) and sensors to collect non-acoustic oceanographic data (see above) can be included in ARs to enhance their capabilities.

3.6.2 Hydrophones

AR developers include as part of their systems hydrophones that are off-the-shelf, customized by other companies for their specific device, or build their own. For example, GeoSpectrum

Technologies (GTI) is a company that designs and manufactures custom acoustic transducers, including directional hydrophones for AMARs (particle velocity sensors, Figure 23, JASCO, 2009b). DASARs use technology developed for DIFAR sonobuoys by Greeneridge Sciences and also include two horizontal, orthogonal directional sensors (particle velocity hydrophones) and one omnidirectional pressure sensor.

HARP developers built a low self-noise, high-gain hydrophone that can pre-whiten ocean ambient noise across four frequency decades (10 Hz – 100 kHz). This is achieved using two separate stages of signal conditioning, one for a low frequency band (10 Hz to 2 kHz) and another for a high frequency band (1 kHz to 100 kHz) (Figure 26). These two stages use different transducers (a single spherical omnidirectional transducer for the high frequency stage and six cylindrical transducers connected in series for the low frequency stage) and provide the ability to record both baleen whale low frequency sounds and high frequency sounds from odontocetes. The signals from these two stages are pre-amplified and pre-whitened (adding more gain at higher frequencies where ambient noise levels are lower and sound attenuation is higher) and then added together via a differential receiver (Wiggins & Hildebrand, 2007). Figure 24 shows the HARP hydrophone system sensitivity as a function of frequency.

Some developers adopt standard field practices that include calibration of all hydrophones before deployment and/or on recovery, others calibrate the entire AR system. Calibration is an important issue and must be addressed for most PAM applications.

3.6.3 Power Supply

ARs operate autonomously and must be powered internally by a set of batteries. AR developers design their systems aiming for low power consumption and include a variety of battery types, sizes and quantities in their systems depending on the desired capabilities and limitations of each design. Different types of batteries are used to power AR systems reviewed here (see Table 2). Each type of batteries has advantages and disadvantages.

Alkaline batteries are cheap but provide less power and are not ideal for high-drain devices because they do not deliver a lot of power quickly but are relatively safe to dispose of. On the other hand, lithium batteries are more expensive (cost twice or more per Amp-hour compared to alkaline batteries) and are toxic to the environment and can cause explosions if short-circuited but last longer the other batteries and are more reliable due to a very low rate of shelf discharge (Bluejay, 2009).

Nickel-Metal Hydride (NiMH) batteries are rechargeable but are less reliable (high shelf discharge rate and inaccurate voltage readings that can result in sudden discharge) and put out less voltage than alkaline batteries. Lead-acid gel cells are also rechargeable but give off potentially explosive gases and are more expensive than NiMH batteries (Bluejay, 2009).

A single AR system may include multiple types of batteries and careful developers use more reliable lithium batteries to power more sensitive or fundamental parts of the instrument (e.g., related to instrument recovery), while using less expensive and safer types, such as alkaline batteries, to power the bulk of the electronics.

3.7 Package Design and External Configuration, Deployment, and Retrieval Issues

Another consideration when using ARs is the choice of system external configuration (shape and size of the package). The choice will depend on: 1) the system capabilities required by the specific application; 2) the environmental conditions and substrate type in the deployment area (type of ocean bottom, presence of strong currents and surface winds, bathymetry, vessel traffic, bottom fishing activities, etc.) and; 3) deployment logistics which include the type of vessels and hoisting equipment available for deployment and retrieval (e.g. winches, cranes, A-frames, and divers), all of which have an impact on the type and configuration of the instrument (or vice-versa).

The internal system configuration will also determine the size of the package which, in turn affects deployment and retrieval issues. The ARs' self-contained power supply constrains the design and capabilities of each system due to tradeoffs between data storage capacity, sampling frequency, and instrument size and depth rating, discussed earlier. We have also already mentioned that the data acquisition rate is indirectly related to power consumption because it determines how frequently the storage media will need to be accessed and written to. For example, the rate at which power is consumed by the HARP data logger is dependent on sample rates and data acquisition sampling schemes (i.e., continuous or non-continuous). Approximately 250 mW is required by the HARP data logger during sampling at the maximum sample rate of 200 kHz, but only about 25 mW when in the non-sampling mode. The HARP storage disks require an additional 2.2 W for one minute while writing data and peak near 5 W upon initial disk spin up (Wiggins & Hildebrand, 2007).

The longer the deployment and the higher the sample rate, the larger the number of batteries that are needed and to a large extent, batteries drive the external design and packaging of an AR system, for instance, in some ARs batteries occupy a significant volume in the housings (e.g., pop-ups, Figure 19), in others, extra pressure cases are used to house the batteries requiring additional instrument flotation to buoy the weight of the batteries during instrument recovery (Wiggins & Hildebrand, 2007). Therefore, the size of the instrument will also change with the number, size, and weight of batteries included, which will, in turn, affect deployment and retrieval logistics and costs.

3.7.1 Depth Rating

Housings to contain AR electronics have depth ratings that specify the maximum deployment depth. Some ARs, like the pop-up (or MARU), have a system depth rating of up to 6,000 m but because of the limitations of the release system (discussed later) the depth rating must be decreased to as shallow as 2,500 m (T. Calupca, personal communication, January 14, 2009). In such cases, the depth rating is environmentally dependent and can be reduced even further due increased noise from high sea states, ocean floor topography, variation in sound speed profile, and natural and anthropogenic sources of noise. In other words, the reduction in depth rating related to most acoustic release systems is very site specific.

Once more, knowledge of the biology of the species of interest, deployment area, and the scientific question asked will dictate the depth rating necessary for the AR. For example, the acoustic behavior of deep diving animals like Cuvier's beaked whales and elephant seals can only be monitored effectively with ARs using instruments that can be deployed at depths below approximately 1,500 m (Johnson et al., 2006).

3.7.2 Instrument Deployment

ARs can be used in moorings, deployed using only a small anchor (e.g., pop-ups, Figure 7B) or used as a stand alone instrument requiring nothing else to be deployed (e.g., ARPs and HARPs, Figures 5 and 6). These configurations can be changed addressing the particular characteristics of the deployment area (depth, currents, bathymetry, etc).

Some areas might already have existing infrastructure for ocean instrumentation in the form of large moorings and other ocean bottom instrument packages that can be used to accommodate fixed ARs (for example, the British Antarctic Survey attached a pop-up in a cage onto a large mooring, Figure 7A). Additionally, existing and planned seafloor ocean observatories are capable of providing power for ARs via a junction box or node and may also provide logistical support in the form of vessels for deployment and retrieval of instruments (see more detailed information on Ocean Observatories in Norris et al., this report). The possibility of using existing infrastructures in oil and gas production platforms as moorings or simple anchoring sites is very interesting and possibly cost effective. Additionally, the availability of auxiliary vessels and highly trained deep diving crews in oil and gas production sites can significantly reduce the operational costs of AR deployment, maintenance and retrieval. The costs/benefits comparison between the use of acoustic releases and having a diving team recover the ARs should be evaluated for each particular area.

Moorings can either be very large with many different components distributed vertically along a line, wire rope or chain (e.g. EARS, Figure 23 and 24), or be a small, "home-made" anchor attached to a line or chain (e.g., TPOD, Figure 12). Moorings can have surface expression (attached to buoys visible at the surface) or be completely underwater (subsurface moorings). Each mooring type has different advantages and disadvantages.

Attaching ARs to large moorings with surface expressions provides the following advantages:

1) Reliability and ease of relocating instruments for retrieval and;

2) Possibility of providing power and data remotely (radio links, see Norris et al. this report).

Disadvantages include:

1) Need for specialized and costly deployment equipment when the size of the mooring is large (large vessels with trained personnel, A-frames, or cranes are required);

2) Possibility of the buoy being a navigational hazard;

3) Possibility of damage and destruction of buoys in areas with natural drifting hazards (e.g., ice in polar areas, Green et al., 2004);

4) Higher total equipment weight and size during deployment and retrieval;

5) Higher visibility to pirates and vandals;

6) Higher susceptibility to the effects of storms or other episodic weather events.

Surface waves and currents introduce considerable drag and tension on the mooring line from bottom to surface. Nevertheless, moorings can be configured with large mooring lines and considerable amounts of flotation and ballast to provide protection from fishing operations and heavy weather/currents ensuring the mooring maintains its position.

Additional requirements to keep large moorings in position, such as flotation and ballast, will make them even larger and will require vessels with heavy lifting capabilities. Smaller moorings can be deployed by divers or from a small boat, and the lifting requirements can be minimized by handling individual components (flotation, data recording electronics, batteries, ballast and release system) at a time.

The increasing need for PAM in shallow water environments, where currents, winds, heavy vessel traffic and other conflicting activities are a concern, will require more reliable moorings. Conventional buoys and mooring systems can require considerable resources to deploy and recover. Surface buoys may attract undesirable human attention, unintended snagging/recovery and/or collateral damage from other marine activities, such as bottom-fishing, especially in coastal areas.

Subsurface moorings can overcome some of these concerns with reduced component size, but they still consists of multiple physical components (anchor-weight, securing line, release, payload and buoyancy unit) and are therefore not usually well suited for deployment from small vessels with limited manpower (Koay et al., 2003). Some subsurface ARs (e.g. pop-ups, AQUAclick, PANDA, DMON) are easily deployed from a small boat by a few people without specialized lifting or hoisting equipment). Nonetheless, there may be a need to use either a diving search team or special acoustic equipment (e.g. transponders and acoustic release mechanisms) during retrieval of these instruments. In cases in which a surface buoy is not used, there are higher risks of losing the instrument because there is no marker at the surface.

Anchoring or mooring is an important consideration for shallow water deployments. Proper anchoring is crucial to avoid equipment loss. Some AR developers provide extensive advice on anchoring (e.g., Chelonia Limited, 2007, 2008: TPOD and CPOD User Guides, Pop-up user's guide and in-house training), while others provide little or none. Prior knowledge of the physical characteristics of the area of deployment is invaluable for determining the type of anchor to be used. The choice of anchor/mooring type and weight depends on anticipated bottom type, depth and currents expected at a site (Koay et al., 2003). A few concrete blocks may not be adequate for a shallow coastal sandy sea bed, as this is a dynamic environment and the instrument package might move due to tidal currents and waves. Massive concrete anchors, digging metal anchors or heavy metal anchors are preferable (Chelonia Limited, 2007).

Anchoring also depends on the size and weight of the instrument being deployed. There is great variation in the dimensions of the instruments inventoried here, from very small and easily handled by one or two people (e.g., PANDA, pop-up, AQUAclick, DMON, EAR, and miniAMAR), to very large instruments such as the ARPs and HARPs that require lifting equipment aboard of the deployment vessels (Figure 5).

The risk of loss, especially for fully autonomous systems, is very high if unreliable mooring systems are used, especially when using directional particle velocity sensors, in which case the suspension method is extremely important to ensure that currents and mooring noise do not affect the sensor (JASCO, 2009b).

3.7.3 Instrument Retrieval

Selection of the most appropriate method for AR retrieval is based upon the water depth, strength of tidal currents and composition of the seabed, as well as on the external configuration of the AR deployed (size, mooring type, etc).

There are many release systems available (mechanical or acoustic), some of them can be quite expensive and in spite of this, are often not 100% reliable. The relative cost advantage and reliability of other methods of instrument retrieval (diver retrieval, grappling) should be considered, in particular in shallow water deployments. For example, the DASAR used by Blackwell and Green (2006) was retrieved by using a double grapnel anchor assembly with 6 m of chain towed perpendicular and across to the line where the DASAR was moored. Figures 27 and 28 show how to use a vertical grapple in detail.

When retrieval by grappling or diving is not an option (or becomes difficult due to weather conditions), a backup release system should be implemented to ensure that a malfunction in the primary retrieval method doesn't translate into instrument and data loss.

An example a mechanical release mechanism is the one on the PANDA that will keep the instrument attached to the anchor but floating at the surface to be retrieved (Figure 29). The

PANDA (Figure 15; Koay et al., 2001) is an example of an AR that is designed to leave nothing on the seabed after recovery and thus provides a system that is ecologically friendly. Some areas (Marine Parks and Marine Protected Areas, for example) require special permits to deploy permanent or semi-permanent instruments in the ocean or on the seafloor. Many also require that all components of the anchor/mooring are removed from the seabed after recovery ("nothing-left-behind"). In addition, the PANDA's release is equipped with an internal leak detector that will trigger an immediate emergency-surfacing sequence in case of leak, avoiding serious damage to the payload and data. Whereas this system has a desirable design, its limitation is that the system cannot be used in depths of over 200 m (Koay et al., 2002).

AR release systems for deep water deployments may include an acoustic release that can trigger a mechanical release mechanism or accelerate the breakage of a corrodible link, or a timed mechanism that can activate the release system at a preset date and time. Pop-ups, ARPs, and HARPs have been retrieved by activation of a burnwire release mechanism. An acoustic command broadcast from the recovery vessel by an underwater speaker causes the release system to apply a voltage between the burnwire and the saltwater ground, accelerating the corrosion of the wire. The corrodible wire link releases the device from the weight and it floats to the surface where it can be either seen or found via a self-contained VHF beacon (included in the pop-up design) (Wiggins, 2003; BRP pop-up user's guide, unpublished; Johnson, unpublished). Two acoustic release systems can be used on the same AR to provide a redundant system and increase the likelihood of instrument recovery in the event of failure of one of the release system (Wiggins & Hildebrand, 2007).

An acoustic release mooring can either disconnect the AR from its ballast weight, allowing the instrument to return to the surface (as mentioned above) or it can release just a tethered buoy that returns to the surface, allowing the rest of the mooring to be pulled up from the tether line. This system has been used on AMARs. JASCO also offers a "nothing-left-behind" option to deploy/retrieve AMARs that has several advantages – no anchors remain on the bottom, and the AMAR remains anchored to the bottom when the float and release surface (ensures it does not get lost after the release is triggered). The third anchor line also remains on the bottom and can be used for grappling if necessary (JASCO, 2009b).

Note that the release systems discussed here are not unique to a specific AR as there are many off-the-shelf options available that can potentially be included in most designs.

3.8 System Customization

AR systems inventoried here may be modified to increase some capability in detriment of another (see Section on Tradeoffs). An AR capability that is usually easily modified is total power capacity. The total system power capacity (Amp-hours) information is not always available in the specifications because most AR system configurations are flexible, allowing the user to either change the number of batteries (e.g. single- and double-bubble pop-ups), or the type of batteries (e.g., alkaline battery packs or longer-lasting lithium battery packs) to accommodate the requirements of a specific application.

Some instruments inventoried also may offer some flexibility in other aspects of its design and configuration to better address requirements of each user's application and deployment area. For example, JASCO has developed a re-usable suite of pressure vessels, suspensions, anchoring systems, and recovery systems that can be customized to meet most requirements (JASCO, 2009b). Therefore, AMARs can be deployed in shallow water using a cement block and be retrieved by a diver, include an acoustic release system for deep water applications, and also have localization capabilities (directional AMAR configuration including a vertical hydrophone array, Figure 14). Another example is the NOAA/PMAEL AUH that has been modified to withstand extreme conditions (~0° C water and strong currents of the Drake Passage). Dziak et al. (2007) doubled the strength of the mooring line and replaced the standard laptop hard-drives with a sealed industrial drive that is rated to -20° C for that application.

The ability to modify or customize the system can be advantageous for the user. Adaptations that have proven reliable in the past should be used if the application so requires, but system modification prior to extensive field use is not recommended, as unforeseen problems in system programming and data management may result in data loss. A change in the instrument software to accommodate recording duty cycles, sampling schemes, or an increase or decrease in the sampling rate can render the system unreliable due to programming errors or limitations of the hardware without sufficient testing. Caution should be used and pilot tests done in the field to assure system reliability after custom changes.

3.9 Noise Issues

Flow and strum noise caused by water motion over the hydrophones or hydrophone can be a problem for ARs in some environments. The DASAR overcomes flow noise using a latex 'sock' secured over an aluminum cage to shield the hydrophone from water motion (Green et al*.,* 2004, Figure 22). Other solutions to this problem include surrounding the hydrophone with a perforated PVC tube (e.g. pop-ups, Figure 7B). Unwanted environmental noise (e.g. sea-surface noise) can also be reduced by pre-conditioning signals via band-pass filters (e.g., HARPs and PALs).

In any AR system, the hydrophones should be free of contact with external objects and the seafloor, and not shielded with acoustically absorbing or reflecting materials (which would impair sensitivity, especially for high-frequency applications). High-frequency sounds have short wavelengths that could be missed if parts of the hydrophone are covered or shielded by components of the AR. These sound shadows should be avoided by placing the hydrophones away from the bulk of the package.

Self-generated noise is also an important concern. One of the key functional constraints of an autonomous acoustic recording system is electronic self-noise (Wiggins, 2003). Instruments that use spinning hard drives or other moving mechanical parts can generate undesired signals in the recordings that can mask sounds of interest. This can also impair or reduce the effectiveness of automated detection and classification of calls (see Oswald et al., this report). The configuration used in ARPs and HARPs keeps the hydrophone well away from any electronic noise generated in the instrument itself (approximately 8.5 m away, Figure 6, Wiggins, 2003). This design has solved the issue of noise produced by the hard drives. The use of non-moving components for electronic data storage (i.e. flash media) is another effective solution (see some examples in Table 2).

3.10 Deployment Configuration of Multiple Autonomous Recorders for Localization, Tracking and Density Estimation of Marine Mammals

Performing mammal localizations can be achieved by using a widely spaced array of omni-directional fixed AR units but it requires synchronized timing of all units. However, it is difficult to obtain precise timing with autonomous underwater recorders, each with its own clock drifting in time independently (Wiggins & Hildebrand, 2007).

AR time-synchronization can be achieved by recording GPS-time linked signals at deployment and recovery to time-align the recorders so that they can provide accurate ranges to detected marine mammals using time delay of arrival techniques. This technology is applicable for localizing acoustic sources such as vessels, seismic sources or baleen whales. The sensors should be spaced appropriately for the desired spatial coverage, signal bandwidths or time resolution, and the expected signal to noise levels (JASCO, 2009b). Cornell's BRP uses sound-based synchronization of multiple pop-ups and proprietary software alignment to achieve the same goals. Performing beginning of the deployment and end of deployment synchronization is normal procedure when using multiple pop-ups in an array. It involves gather all the units close together, usually in a circle on a boat deck, making a set of sharp tones and accurately recording the onset times. This simple procedure allows chronological matching of the recordings of all the units during the entire duration of the deployment.

Directional ARs (DASAR, AMAR DV) provides the ability to obtain a bearing to detected sounds without using arrays of recorders. By using an array of these sensors spaced hundreds of meters apart cross-fix bearings and time delay of arrival data can be obtained and can provide localizations for sources that have lower energy levels. A single directional recorder can be used to track bearings of a source. Using target motion analysis techniques the bearings can be converted into a localization and track over time (JASCO, 2009b). Calibrations with known position sounds can be very important to the success of the triangulation approach to sound source localization (Green et al., 2004).

Recently advances in density estimation models indicate that deploying many (inexpensive but storage or bandwidth limited) fixed ARs is a better approach than deploying a few long duration/high bandwidth AR units. The choice also depends on what species are being targeted, but even so, if a single or a few species that produce high-frequency clicks are of interest, it may be more cost-efficient to use sound detectors (AQUAclick, PAL, CPOD and TPOD) than high frequency continuous recorders (HARPs). Additionally, if the area of deployment is very deep, the depth rating and retrieval system of these instruments may be limiting the choices available.

3.11 Instrument Theft and Vandalism

Theft and vandalism can be a serious risk to AR retrieval in some areas. Some solutions include obtaining cooperation and advice from local fishermen; using a very small marker with minimal surface expression or subsurface moorings; using acoustic transponder releases; using corrodible links that dissolve after a predetermined time in the water and then release a recovery buoy from the bottom; and using divers to deploy and recover the instruments (TPOD/CPOD User Guide). Offering a reward might improve the likelihood to recovering a lost instrument, sometimes even after long periods of time (R. S. Sousa-Lima personal experience with one pop-up found and returned by a fisherman after a year). The most effective and reliable solution is usually some combination of these solutions.

3.12 System Availability to Users

The pricing and availability of the PAM systems inventoried here varies depending on the type of organization which is providing access to the technology. Private companies usually have a relatively straight forward pricing and purchasing process (providing user support through manuals and/or staff) while some developers from academia, research, and government institutions have more customized agreements for use, lease or purchase of their AR systems. Many of these institutions also have technical staff to provide additional data processing services. Pricing also varies depending on the time demands and also on the amount and type of data processing and analyses provided. For example, some groups will tailor the pricing to adapt to a broad customer audience that varies from small collaborative research efforts (usually long-term, small scale) to oil and gas industry contracts (short-term, rapid turn around, high demand).

High costs restrict the number of units that can be deployed and thus reduce the system's usefulness as a monitoring tool (Lammers et al., 2008), especially when array configurations are needed to estimate relative numbers and distributions. Some ARs are available for lower costs in order to make them more accessible for applications that require multiple units (ex: EAR, Lammers et al., 2008).

Availability of multiple devices in a timely manner depends mostly on the technology providers, but also on their suppliers. Devices that have high demand must have production capabilities that meet the users' demands. In most cases, private businesses that offer a product or product line are better able to meet high demands for their products, but in some cases government and academic agencies can provide high quantities for their own or other users' needs.

4 Discussion

Considerations regarding equipment and study design should include the frequency band of sounds produced by the species of interest, the areas and scale over which monitoring is intended, background noise levels, and the specific goals of the study or monitoring effort. For example, a system intended to detect the occurrence of animals near a platform could consist of several independent PAM systems, whereas one intended to localize and track animals using their calls would likely consist of a synchronized hydrophone array with spacing that would allow tracking over ranges of interest.

ARs can be used in every step of a well designed PAM study. ARs are extremely valuable for the early stages of acoustic prospecting, when information can be gathered *before* E&P activities begin. The timing of changes in relative numbers of animals is important information which can be used to schedule exploratory activities (e.g. seismic studies); as well as determine the effects of production and transportation activities on animal distributions. In most cases, the required resolution of this information is very crude and knowing the relative occurrence of animals is sufficient for planning purposes. The next section will discuss the use of ARs during the development of PAM studies in areas of planned oil and gas exploration and production activities.

ARs are an effective method of acoustic monitoring of marine mammals, and especially for identifying which species are present in a given area at a given time (e.g., Clark & Charif, 1998; Nieukirk et al., 2004; Heimlich et al., 2005; Stafford et al., 1999, 2007; Mellinger et al., 2007; Širović et al., 2009), locating and tracking individuals (e.g., Sousa-Lima & Clark, 2008, 2009), identifying sounds associated with different regions (Stafford et al., 1999, 2001), and determining patterns of distribution and relative abundance (Mellinger et al., 2004a, 2004b).

Among the main constraints of analyzing and interpreting acoustic data collected using ARs is the difficulty of associating the number of sounds recorded with the number of animals present, the detection range and location of the sounds, as well as the seasonal, behavioral, and demographic variations in the calling behavior of different species (Clark & Charif, 1998; Mellinger & Barlow, 2003). The extent to which these types of information can be obtained depends on how the study design took environmental and biological aspects into account and on how AR units were deployed (the number of units deployed and the geometric spatial arrangement of the ARs).

Fixed PAM will continue to be one of the most cost-effective ways to remotely monitor marine mammal species and their surroundings, and to collect data on how human activities are affecting these dynamic systems. McDonald et al.'s (1995) study incidentally detecting whale calls using OBSs also recorded noise from seismic air guns and from ship traffic. This is a good example of how ARs can be effective for monitoring noise produced by oil and gas exploration and production activities while also monitoring the occurrence, acoustic behaviors and movements of animals in the area.

The demand for offshore petroleum and gas will provide many opportunities to study the effects of oil and gas exploration and production activities on marine mammals. Underwater sounds produced by exploration and production activities are superimposed onto an already dynamic and complex acoustic marine environment. The world's ocean can be seen as a mosaic of areas with different animal acoustic ecologies and levels of human disturbance. This mosaic of soundscapes provides opportunities to acoustically compare the effects of noise across different areas with different levels of disturbance within a similar habitat (e.g. whale breeding areas in pristine and disturbed areas), and within a particular area across time (e.g. before, during and after study designs in areas with planned oil and gas exploration and production activities). Fixed PAM technologies such as ARs are well suited for these types of investigations. From AR data, statistical models can be derived to explain the effects of many naturally occurring and anthropogenic phenomena (e.g. Sousa-Lima & Clark, 2008).

4.1 The Use of Fixed Autonomous Recorders in Marine Mammal Monitoring and Mitigation during Oil and Gas Exploration and Production Activities

4.1.1 Seismic Surveys

Some regions in the world that are important for oil and gas exploration are also areas of occurrence of living marine resources including marine mammals. When baseline data on species occurrence and seasonality exists, these data should guide the choice of fixed AR systems used. When such information is not available, AR systems should be deployed ahead of time (ideally commencing as soon as the area becomes of interest to the O&G industry and continuing for at least one year) to facilitate data collection on the seasonality of the species occurrence. This information is essential to inform the choice of AR system(s) used to monitor a particular area. In all cases, the bathymetry of the area to be monitored must also be taken into account. Very shallow areas can be monitored using AR systems that are deployed on or near the ocean bottom (such as the AQUAclick, pop-ups, and the EAR) thus avoiding mooring lines that can be a hazard to the towed seismic array. These PAM systems should be able to record broad band frequencies to gather information about as many species of marine mammals that might be present as possible. A high sampling rate means increased power supply and storage capacity demands, which tend to increase the cost of a system. For greater coverage or for sampling among several locations simultaneously, less expensive equipment can be deployed in a multi-sensor array. More sophisticated and costly AR packages could be used whenever their unique capabilities, such as continuous recordings at high-sampling rate (e.g. HARPs), are in demand to target specific locations, species, or both.

The ample distribution of seismic exploration activities in many areas in time and space should provide ample opportunity to plan and carry on controlled experiments in collaboration with the O&G industry to identify the effects of the seismic activities on the natural variation of the observed behavior and/or distribution of marine mammals. Opportunistic experiments to determine the effect of seismic surveys on marine mammal vocal behavior can also be conduced while seismic exploration is occurring using ARs (e.g., Nieukirk et al., 2004; Di Iorio & Clark 2010). Both planned and opportunistic experiments should take into account biological and environmental factors that vary spatially (e.g., bathymetry and water temperature that affect sound speed profiles and marine mammal food resources) and may influence the natural fluctuations in occurrence and vocal activity of marine mammals.

4.1.2 Construction and Installation of Platforms and Seabed Production Units

Activities associated with the construction and installation of platforms and other production units generate underwater noise. Blackwell & Greene (2006) determined the levels, characteristics, and range dependence of underwater and in-air sounds produced by the Northstar oil development, located in near shore waters of the Alaskan Beaufort Sea. Vessels (crew boat, tugs, and self propelled barges) were the main contributors to the underwater sound field and were often detectable as far as 30 km offshore. When vessels were not operating, broadband noise from the Northstar rig reached background values at a distance of 2 - 4 km from the source. Northstar sound levels showed more variation during construction of the island than during drilling and production.

The typical occurrence of multiple platforms in an oil production area would allow multiple ARs to be mounted on or close to the platforms, providing a cost-effective way to deploy an array of ARs. This could increase the capabilities of the hydrophone system to allow much greater geographic coverage and easy maintenance, but also allow the possibility of tracking of individual animals and groups. To do this it is necessary some knowledge of the sound propagation properties and underwater noise budget of the deployment area, so that hydrophones can be deployed in such spatial configuration that would allow acoustic coverage of the area of interest within which the same sounds from vocalizing individuals can be detected on multiple hydrophones (at least 3). Continuous time-synchronization of these hydrophones could be achieved very effectively by monitoring the exact location and times of acoustic events that could be detected by all hydrophones. These acoustic events need not be application-specific and could be existing transient noises generated by the normal activities of the production platform.

4.1.3 Oil and Gas Transportation

Vessel traffic has been determined to cause disturbances in the behavior of several species of marine mammals, including humpback whales (Sousa-Lima & Clark, 2008, 2009), gray whales (Bryant et al*.,* 1994), blue and fin whales (McDonald et al., 1995), belugas and narwhals (Finley et al., 1990), to name a few**.** Additionally, shipping noise (i.e. background noise from shipping-vessel traffic) is the most important contributor to the increase in ocean background noise levels over the last decades (McDonald et al*.,* 2006). The transportation of any commodities (not only oil and gas) in vessels is contributing to overall noise pollution in areas far removed from the production activities. Fixed PAM using ARs in areas around shipping lanes can be an effective way to monitor how this source of noise is potentially affecting existing populations of marine mammals by measuring how much of their acoustic habitat is being lost (Clark et al., 2009).

4.2 Potential Areas for Further Development

4.2.1 Increased Power Capacity and Low-Power Electronics

Wiggins and Hildebrand (2007) point out that as larger capacity disks become available (Figure 30), longer deployments at higher sampling rates will be possible. This will require additional batteries which in turn will mean additional weight that will need to be compensated for with additional buoyancy. On the other hand, lower power electronics and faster data transfer rates from the memory buffer to data storage disks (i.e., disks are powered for shorter periods) or flash memory cards, could provide alternative means for longer deployments with the same or fewer batteries and lighter components. Several developers are planning for higher capacity systems, for example, JASCO expects to make available new 512 GB memory modules to accommodate up to 8 TB of memory in the summer of 2010 (JASCO, 2009b).

The advancement of consumer digital electronics (music players, cellular phones, cameras, etc.) has resulted in dramatic improvements in memory high-capacity solid-state and low-power processer memory. Microprocessors with lower power consumption would allow longer deployment periods and/or higher sampling frequencies. These advancements are going to be extremely important in future AR technologies and will affect all aspects of AR design and configuration. This will result in lower data storage costs, power requirements, and faster data-transfer and writing rates. Eventually, flash storage media will replace the energy-intensive, motorized disk drives currently used (e.g., next generation pop-ups; T. Calupca, personal communication, January 14, 2009).

Higher energy capacity batteries (e.g., lithium chemistry) will likely be used to provide extra power with the same number of batteries. Until these higher power batteries are used in the ARs, an alternative approach suggested by Wiggins & Hildebrand (2007) is to house the extra alkaline batteries separately from the housing containing instrument electronics and to jettison the battery pack during instrument recovery. This would result in less required buoyancy and smaller instrument packaging.

The road forward points to a reduction in instrument size and an increase in system capabilities. The use of solar cells on surface moorings is also a possibility for increasing deployment duration without increasing size. Other capabilities, such as USB interface for data downloading and rapid battery recharging already implemented in some systems (e.g., AQUAclick and AMAR) allows quick download of the collected data without having to open the main housing. This capability optimizes ship time and reduces the deployment and retrieval costs significantly (Shariat-Panahi et al., 2008) and more efficient ways to accomplish this should be explored.

4.2.2 Information Networks and Integration

In the 15th century, Leonardo da Vinci conducted the first underwater communication study. By using an underwater ear to hear the sound of distant ships, Da Vinci discovered the possibility of long-range underwater sound propagation. The first practical implementation of a wireless underwater communication system was delayed until 1945, when a single sideband underwater telephone was developed. Underwater networks of acoustic relays using wireless modems and receivers with networking capabilities (AquaNetwork: DSPComm), uncabled autonomous near-real-time systems, or acoustic links offer new ways to communicate data in underwater channels. Ocean observatories are profiting from these possibilities to integrate underwater information (see Norris et al., this issue). Details on this technology are beyond the scope of this review but this should be regarded as a fertile ground for advancements in PAM systems.

4.3 Concluding Remarks

The wide range of AR capabilities reviewed here is the result of different application needs that have dictated the design and configuration of ARs. AR original applications were not necessarily directed at servicing O&G industry as they were mostly built for achieving specific research objectives and non-commercial purposes. As the research demand increased, developers expanded AR capabilities to collect acoustic data for longer periods, in more remote areas, and covering as many species as possible (C. W. Clark, personal communication, November 28, 2009). Monitoring and mitigation requirements from regulatory institutions, that the O&G industry must adhere to, will be better achieved as the existing technology develops.

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5 Tables

Table 1. Inventory list of fixed autonomous acoustic recording devices, including acronyms, developers and sources of information.

Acronym	System name	Developers	References listed by date
AAR on a MFP or "Insta-array"	Autonomous Acoustic Recorder arranged as sensors in a Portable Matched-Field Processing System or "Insta-array"	Marine Physical Laboratory (MPL), Scripps Institution of Oceanography (SIO), Greeneridge Sciences, Inc., University of Queesland, and the Defence Science and Technology Organization, Defence Department of Australia	Thode et al. (2006)
Acousonde™ (tag)	Replaced the Compact Acoustic Probe (CAP) or Bioacoustic Probe (Bio-probe)	Greeneridge Sciences, Inc.	Burgess et al. (1998); Burgess (2000); Au et al. (2000); Acousounde (n.d.)
AARS	Autonomous Acoustic Recording System	National Sun Yat-sen University, Kaohsiung, Taiwan	Ming-Hao et al. (2007)
AHS, AUH, OBH, or Haruphone	Autonomous Hydrophone System, Underwater Hydrophone, or Ocean Bottom Hydrophone	National Oceanic and Atmospheric Administration's (NOAA) Pacific Marine Environmental Laboratory (PMEL) , and Oregon State University (OSU)	Stafford et al. (1999); Fox et al. (2001); Fowler (2003); Nieukirk et al. (2004); Mellinger et al. (2004a, 2004b); Heimlich et al. (2005); Mellinger et al. (2007); Dziak et al. (2007)
AQUAclick	NA	Aquatec Group Limited, Hampshire, UK	Kyhn et al. (2008); AQUATEC (n.d.)
AMAR	Autonomous Multi-Channel Acoustic Recorder	JASCO Research Ltda, Canada	JASCO (2009a); JASCO (2009b)
ARP	Acoustic Recording Package	Scripps Institution of Oceanography Whale Acoustic Lab (SWAL)	Wiggins (2003); Gedamke (2005); Munger et al. (2005); Gedamke et al. (2007); Širović et al. (2009); Oleson et al. (2007); Wiggins and Hildebrand (2007); Stafford et al. (2007)
A-TAG (tag)	Acoustic tag	Marine Micro Technology, Japan	Akamatsu et al. (2000); Akamatsu et al. (2005); Wang et al. (2005); Akamatsu et al. (2008); Kimura et al. (2009)
AUAR	Autonomous Underwater Acoustic Recorder	V.I.Ili'chev Pacific Oceanological Institute in Russia	Acoustics (2004); Borisov et al. (2008)
AULS	Autonomous Underwater Listening Stations	Clifford Goudey, MIT Sea Grant, Center for Fisheries Engineering Research (CFER) and Rodney Rountree, UMass/Dartmouth and Tony Hawkins, University of Aberdeen, King's College, UK	MIT Seagrant (n.d.); DOSITS (2008)
AURAL	Autonomous Underwater Recorder for Acoustic Listening	Multi-Electronique Inc., France (MTE)	Simard et al. (2008); MTE (2009)
AUSOMS-D	Automatic Underwater Sound Monitoring System	System Intech Co., Ltd, Tokyo, Japan	Shinke et al. (2004); Ichikawa et al. (2006); Tsutsumi et al. (2006)
CritterCam (tag)	Video camera	Greg Marshall with support from National Geographic	Marshall (1998); Calambokidis et al. (2007)
DASAR	Directional Autonomous Seafloor Acoustic Recorders	Greeneridge Sciences, Inc. incorporated DIFAR sensors from Sparton Electronics, FL into DASARs.	Norman and Greene (2000); Greene et al. (2004); Blackwell and Green (2006)
DGS-Ocean	Ocean Digital Spectrogram Recorder	Loggerhead Instruments	Loggerhead Instruments (2010)
DMON	Digital Acoustic Monitor	Woods Hole Oceanographic Institution (WHOI)	A. Bocconcelli, personal communication, October 17, 2009); Johnson, unpublished
DTAG (tag)	Digital Acoustic Tag	Woods Hole Oceanographic Institution (WHOI)	Johnson and Tyack (2003); Tyack et al. (2006); Arias et al. (2008)
EAR	Ecological Acoustic Recorder	Marc O. Lammers (Oceanwide Science Institute - OSI) and Kevin Wong, NOAA Fisheries, Pacific Islands Fisheries Science Center, Coral Reef Ecosystem Division (CRED), Hawaii.	Lammers et al. (2008)
HARP	High-frequency ARP	SWAL	Wiggins and Hildebrand (2007); Baumann et al. (2008)
LARS-LF and –HF	Long Term Acoustic Recording Systems (Low and High Frequency)	David Mann, University of South Florida (USF)	DOSITS (2008)
LADC EARS	The Littoral Acoustic Demonstration Center Environmental Acoustic Recording System	Naval Oceanographic Office (NAVOCEANO)	Newcomb et al. (2002); Ioup et al. (2009); Newcomb et al. (2009); J. Newcomb and G. Ioup personal communication, 30 November 2009
OAR (tag)	Onboard Acoustic Recorder	Stacia Fletcher, Department of Biology and Institute of Marine Sciences, UC, Santa Cruz	Fletcher et al. (1996)
PAL	Passive Aquatic Listener	University of Washington's Applied Physics Laboratory (APL). Available commercially through RSL (Environmental Remote Sensing Technologies Ltd.) in Athens, Greece	Nystuen (1998); Nystuen (2006) Nystuen et al. (2007); J. Nystuen, personal communication, November 15, 2008
PANDA	Pop-up Ambient Noise Data Acquisition	Acoustic Research Laboratory (ARL) of Tropical Marine Science Institute in National University of Singapore	Koay et al. (2001); Koay et al. (2002)
Pop-up or MARU	Marine Acoustic Recording Unit	Bioacoustics Research Program (BRP) at the Lab of Ornithology (CLO), Cornell University	Calupca et al. (2000); Clark et al. (2000); Clark et al. (2002); Sousa-Lima and Clark (2008, 2009); T. Calupca, personal communication, January 14, 2009, BRP, unpublished
RASP	Registratore Acustico Subacqueo Programmabile	Nauta Ricerca e Consulenza Scientifica, Italia	NAUTA (n.d.)
RUDAR™	Remote Underwater Digital Acoustic Recorder	Cetacean Research Technology	Cetacean Research Technology (2010); J. R. Olson, personal communication, February 1, 2009
µRUDAR™	Micro Remote Underwater Digital Acoustic Recorder	Cetacean Research Technology	Cetacean Research Technology (2010) ; J. R. Olson, personal communication, October 20, 2009
T-POD and C-POD	NA	Chelonia Limited, U.K	Watkins and Colley (2004); Chelonia Limited (2007); Chelonia Limited (n.d.); Kyhn et al. (2008)
USR	Underwater Sound Recorder	CMST – Centre for Marine Science and Technology, Curtin University, Australia	CMST (2008)
UTDRT (tag)	Ultrasound Time/Depth-Recording Tags	Peter Madsen, Department of Zoophysiology, Institute of Biological Sciences, University of Aarhus, Denmark	Madsen et al. (2002)

Table 2. Summary table outlining the main capabilities and specifications of each system (NA = information not available).

Instrument	Dimensions	Maximum deployment depth (m)	Maximum deployment time	Sampling frequency (Hz)	Power supply and energy capacity	Data storage	Data format	Microprocessor	Examples of species studied
AAR	20 cm x 2.5 cm for each recorder	2,000	71 hours	2,000 (100-20,000)	alkaline battery pack	1GB Flash memory	MT files, Depth, Tag temperature 2-D acceleration/tilt	NA	*Megaptera novaeangliae*
AARS	NA	NA	4.5 hours	69,000	16V lithium cells	Hard disk	NA	PC-104 single-board computer (Celeron 1G)	NA (tested in the field with noise)
Acousonde™ (tag)	22.1 x 3.2 cm	3,000	23 days (at 2 kHz)	25,793 (low-power channel) 232,000 (high-frequency channel)	lithium battery pack	8 GB	2 acoustic channels, MT files, Depth, Tag temperature 2-D acceleration/tilt (option)	Tattletale Model 7 on earlier version (Bioacoustic probe)	*Megaptera novaeangliae, Mirounga angustirostris*
AHS, AUH, OBH, or Haruphone	1.8 x 0.17 m	4,000	1 year 14 days	100 900	alkaline battery pack	4 GB hard drives	Spectrograms	NA	*Balaenoptera edeni, B. musculus, B. physalus, B. acutorostrata, Eubalaena glacialis, Megaptera novaeangliae,* and other non-identified baleen whales
AQUAclick	240mm long x 88mm diameter	100	until storage capacity is reached	50,000-170,000	NiMh rechargeable batteries	8 MB standard memory	Click parameters stored are: occurrence time, duration, and sound level	NA	*Phocoena phocoena*
AMAR	Standard: 28 x 7 inches; 80 lbs	400	50 days	Up to 128,000	alkaline or lithium batteries	Solid State storage. 128 GB base, expandable to 2 TB or more	1-2 channel WAVE files with non-acoustic data (temperature and 3-axis orientation are standard, high-precision orientation, ADCPs, turbidity, depth or any other analog, RS-232, or RS-485 system on request)	NA	*Balaenoptera physalus*, *Balaena mysticetus*, *Eschrichtius robustus*, *Orcinus orca*, *Delphinapterus leuca*, *Odobenus rosmarus*, *Erignathus barbatus*
ARP	1.5m by 1.5m by 1.5m plus a 10m long line and flotation for the hydrophone	Up to 7,000	~ 400 days	1,000	alkaline or lithium battery pack	72 GB hard disk drives	time series, spectra, or spectrograms	Ocean Sensors OS500 data logger (http://www.oceansensors.com/) 20MHz	*Balaenoptera musculus*, *B. physalus*, *B. bonarensis, Megaptera novaeangliae, Eschrichtius robustus*, *Balaena mysticetus, Eubalaena japonica*
A-TAG (tag)	125 x 73 x 21 mm	300	75 days	300,000	lithium battery cell	256MB flash memory	Click intensity, timing and the difference in time arrival between two hydrophones	NA	*Neophocaena phocaenoides asiaeorientalis*
AUAR **	Weight=145 kg	50	30 days	15,000	Three sealed gel batteries with a capacity of 115 Ah	Records data on a 1 GB Flash disk then writes it onto a 160GB hard drive	Analog sound data	*Prometheus* single board PC/104 computer manufactured by Diamond Systems Corporation	*Eschrichtius robustus*
AULS	NA	200 or 1,800 (not tested)	57 hours	11,000-44,000	lead-acid gel cells	10 GB hard drives	WAVE files	NA	fish
AURAL	With 16 batteries: 14.6 x 82.5 cm and 16kg; with 128 batteries: 14.6 x 178 cm and 45 kg	300	Many months	2,048-32,678	alkaline battery pack	Combined 64MB Flash and 60GB hard drive	WAVE files, temperature and depth	33 MIPS Dallas DS89C450 Ultra High Speed Flash Microcontroller	whales in the St. Lawrence River
AUSOMS-D	NA	NA	NA	44,100	NA	NA	2 acoustic channels	NA	*Dugong dugon*
C-POD*	Length: Early versions: 8 D-cells, 535 mm. Current version: 10 D-cells, 655 mm. Diameter: 90 mm 8 alkaline. Weight: D-cell version: 1.7 kg without batteries, 2.9 kg with batteries; 10 alkaline D-cell version: 2.0 kg without batteries, 3.4 kg with batteries.	100	4 months	20,000-150,000	alkaline battery pack	Removable high-density secure digital memory cards (SD cards)	Click center frequency, frequency trend, duration, intensity (8 bit), bandwidth, envelope slope, angle of the POD to the vertical, and temperature	Altera MAXII	All odontocetes except sperm whales (*Physeter macrocephalus*)
DASAR	Cylinder of 30 by 36 cm	30	45 days	2,400	alkaline battery pack	30 GB disk drive	3 channels provide azimuthal bearings to sound sources	Persistor Instruments Inc. (Bourne, MA) single-board computer, model CF1 with a Persistor Instruments ''BigIdea'' IDE controller	*Balaena mysticetus*
DS-Ocean	NA	100 m for PVC housing and 2,000 m for Aluminum housing	NA	80,000 Burst recordings of up to 400,000	alkaline battery pack	32GB Secure Digital High Capacity (SDHC) memory	WAVE files	dsPIC33F	invertebrates, fishes, and marine mammals
DMON	70 mm (2.8") diameter x 215 mm (8.5") Weight (air): 1.5 kg Weight (salt-water): 400 g	1,500	LF 50 days MF 180 hours	Examples of three possible frequency settings: LF 80,000 MF 240,000 HF 480,000	Rechargeable Li-Ion battery	32 GB Flash Memory * * *	Sound files (3 independent acoustic channels), temperature, depth and orientation	TMS320VC5509A DSP	Fish and Cetaceans
DTAG (tag)	5 x 12 cm (attached to a GPS equipped buoy)	2,000	determined by its memory capacity and audio sampling rate	2,000-20,000	lithium battery	Up to 3 GB Flash memory	Sounds, depth, temperature, and orientation.	NA	*Eubalaena glacialis, Physeter macrocephalus, beaked whales*
EAR	10.16-cm-diam by 60-cm long cylinder	500	1 year	2—64,000 (max)	alkaline battery pack	flash memory card periodically transferred to a hard drive	binary files	Persistor CF2 microprocessor, a 1 Gbyte compact flash card, a Persistor BigIDEA IDE adapter	*Stenella longirostris*
HARP	six 30.5cm diameter glass spheres plus a 10m long line and flotation for the hydrophone	~ 7,000	55 days OR 1 year	10-200,000 OR 30,000	alkaline or lithium battery pack	16 high-capacity integrated drive electronics (IDE) laptop disk drives	XWAV time series files	32-bit, 20MHz microcontroller from Motorola (http://www.motorola.com)	*Tursiops truncatus, Stenella longirostris, Peponocephala electra, Mesoplodon sp*
LARS-LF and LARS-HF	NA	NA	1 year 2 months	3,333 44,100	NA	Flash memory	NA	NA	Fish and dolphins
LADC EARS	8.5 inches in diameter and 24-3/8 inches long, 100 lb	3,000	14 days at max sampling frequency >66 days at 11,700 Hz sampling frequency	50 – 192,000 (max)	alkaline D-cells	4 IDE 2.5-inch disk drives	NA	NA	*Physeter macrocephalus*
OAR (tag)	17.08x12.70x6.67 cm	800	6 days	20-14,500	alkaline batteries	Digital audio tape (DAT recorder)	Sound files	NA	*Mirounga angustirostris, Zalophus californianus*
PAL *	30 inches long by 6 inches in diameter	1,000	1 year	100-50,000	alkaline or lithium battery pack	2 GB flash memory card	Binary restored to time series (sound bites)	Tattletale Model 8	*Orcinus orca*
PANDA	30 kg without anchor	200	9-10 days	10-10,000	rechargeable lithium video camera batteries	12 GB Hard drive	Time series	Persistor-based MCU system with processing power of an 80386 CPU	NA
Pop-up or MARU*	Single sphere: 48.3cm high and 58.4cm diameter Double-bubble: 100cm high and 58.4cm diameter	2,500 (acoustic release dependent) Up to 6,000 (on moorings)	90 days	2,000-64,000 (max)	alkaline battery pack (Double-bubble configuration doubles power capacity)	120 GB hard drive	Binary restored to sound files (aiff)	Tattletale Model 8 and analog to digital conversion board made by Onset Technologies	*Balaenoptera musculus*, *B. physalus*, *B. bonarensis, Megaptera novaeangliae*, *Eubalaena glacialis*
RASP	9 x 50 cm	500	184 hours maximum	Up to 48,000	battery pack NiMH fast rechargeable	4GB compact flash cards (8GB available)	WAVE or MP3 files	Modified MicroTrack 24/96 pocket recorders with an original time control board	Whales and dolphins
RUDAR™	17.8 cm, 80lbs or 100lbs with batteries	1,500 or 3,500	Depends on sample rate chosen	Selectable sampling rates up to 192,000	rechargeable Lithium Ion batteries	compact flas cards for short deployments and hard disks for longer deployments	up to 4 hydrophone channels	Sound Technology ST1400ENV mobile data recorder & sound level monitor	Cetaceans
μRUDAR™	13" long by 4" diameter	250	10 hours	96,000	NA	16GB industrial-grade compact flash memory card	up to 4 hydrophone channels	M-Audio MicroTrack II digital recorder	Cetaceans
T-POD	Length: 0.86 m Diameter: 0.90 m; 2.8 kg with no batteries; 4.4 kg with 15 alkaline D cells	Center-opening: 150 Deepwater: 2,500 (tested) 3,500 (not tested)	1 year OR until storage capacity is reached	200,000	alkaline battery pack	128 MB memory	Click start and end times, battery voltage, angle of the POD to the vertical, system noise, and temperature	Altera MAXII	*Phocoena phocoena*
USR	114 x 900 mm, weight = 30 kg (size options are available)	NA	2 years	NA	NA	one or two 2.5" hard disk drives and/or Type 1 Compact Flash Card	1 or 2 hydrophone channels	NA	Fish, marine mammals and noise
UTDRT (tag)	NA	1,100	30 minutes	62,500	NA	192 MB Compact flash card	Sound files, realtime and depth	Maxim Integrated Products, Inc. DS5000T	*Physeter macrocephalus*

* New versions or capabilities are in development.
** The information given here is for a radio transmitting version of the AUAR: T-AUAR (Borisov et al., 2008).
*** 64 GB capacity possible in 2010 (Johnson, unpublished)

Table 3: Deployment times (in days) for pop-up or MARU (version 2) (Cornell BRP, unpublished).

Typical Deployment Time in Days for V2 Pop-Up using 120GB Drive										
Maximum Recordable Frequency (Hz)	Necessary Sampling Rate (Hz)	Single Bubble				Double Bubble				
		Duty Cycle (%)								
		100	50	25	16.6	100	50	25	16.6
500	1,000	150	164	171	174	365	398	417	424
1,000	2,000	110	120	126	128	270	295	309	314
2,000	4,000	55	60	63	64	135	147	154	157
4,000	8,000	25	38	50	56	60	90	120	135
8,000	16,000	23	35	46	52	43	65	86	97
10,000	20,000	18	27	36	41	35	53	70	79
20,000	40,000	17	26	34	38	17	26	35	39
32,000	64,000	11	17	22	25	11	16	22	24

max deployment limited (365 days until possible burn assembly deterioration)
SCCB battery limited (220 days for single, 660 days for double)
main battery limited
hard drive limited

6 Figures

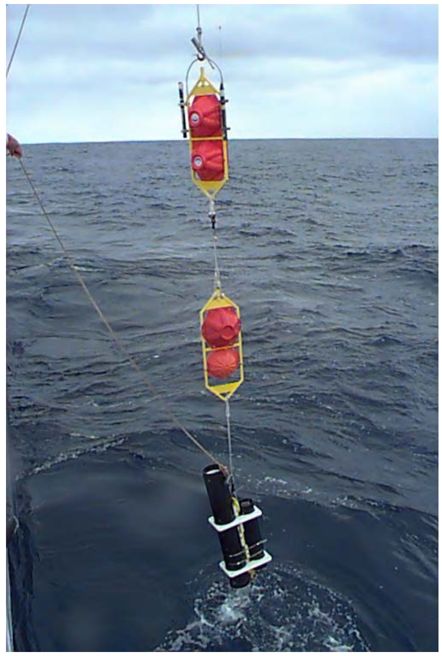


Figure 1. Deployment of a LCHEAPO autonomous recorder (Retrieved in 2008 from http://www.mpl.ucsd.edu/obs)

Figure 2. μRUDARTM (Retreived from Cetacean Research Technology - http://www.cetaceanresearch.com/hydrophone-systems/rudar/index.html).

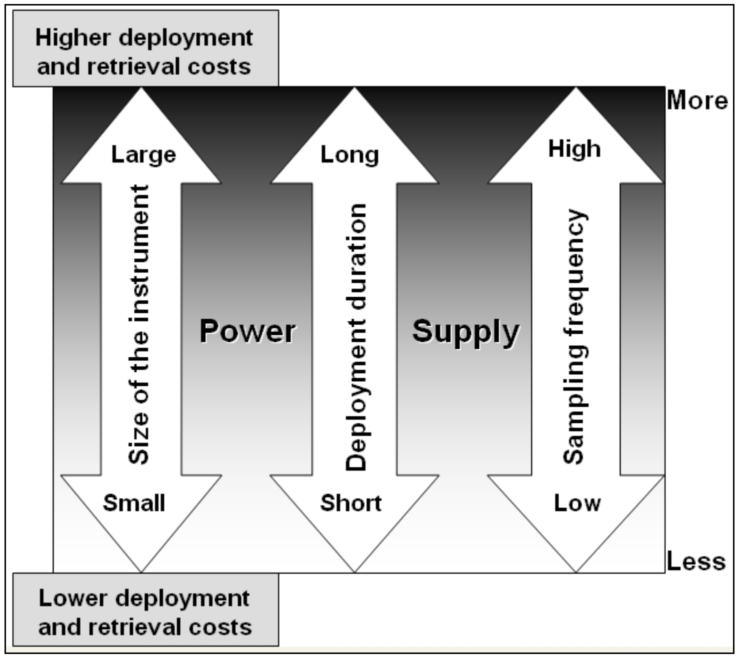


Figure 3. Schematic of the tradeoffs among power supply, sampling frequency, deployment duration, size and deployment and retrieval costs. Less power supply will limit AR sampling frequency and deployment duration, but in turn will result in a smaller instrument package and decrease deployment and retrieval costs.

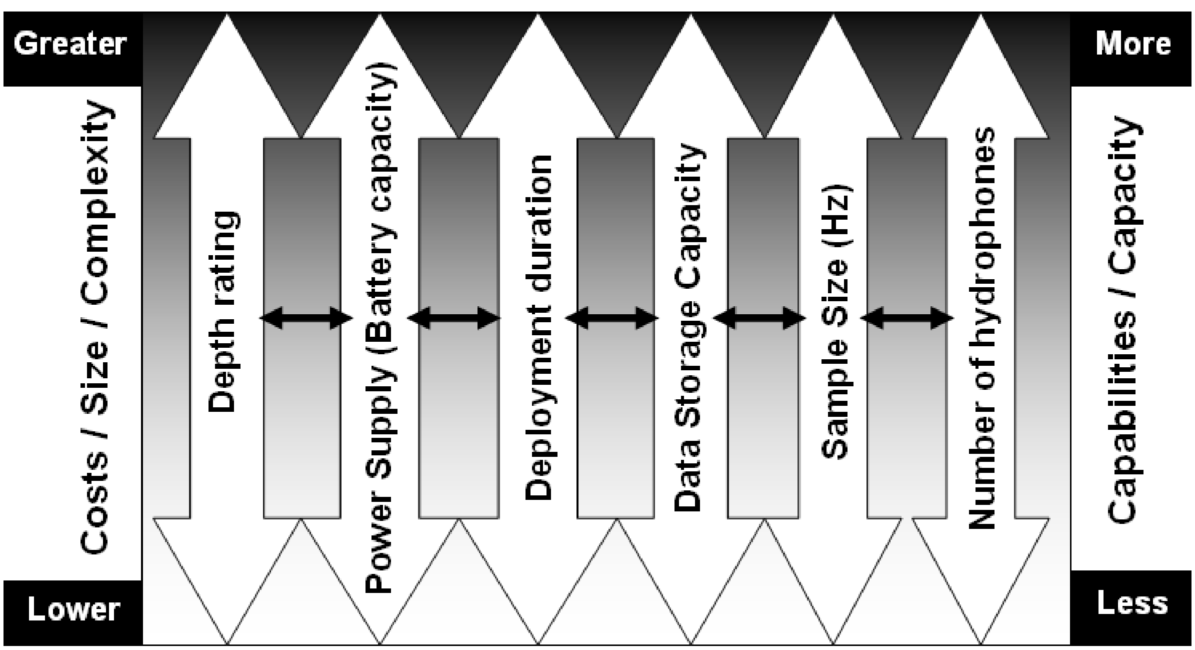


Figure 4. Schematic of more tradeoffs among capabilities and limitations of AR systems.

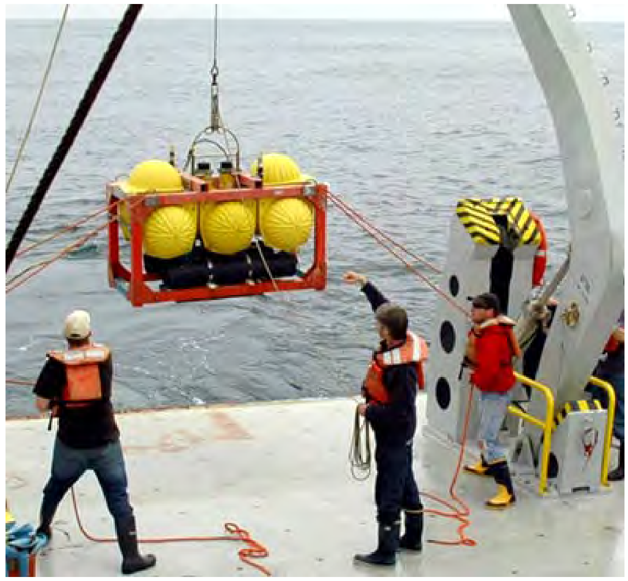


Figure 5. Photograph of a HARP (HARPO version) being deployed (Retrieved from http://cetus.ucsd.edu/technologies_HARP_Packaging.html).

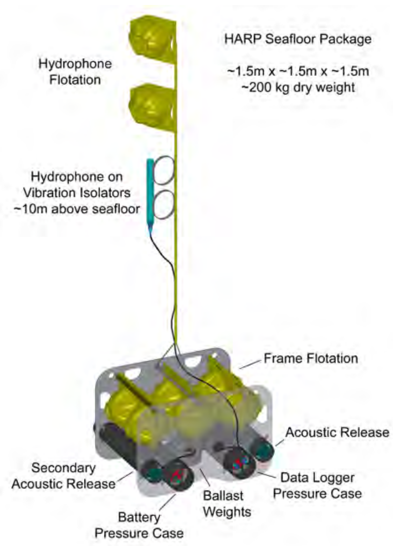


Figure 6. HARP V3 - HARP Seafloor package including data logger and acoustic release electronics pressure cases, ballast weights, glass flotation sphere in yellow hard hats (Wiggins & Hildebrand, 2007).

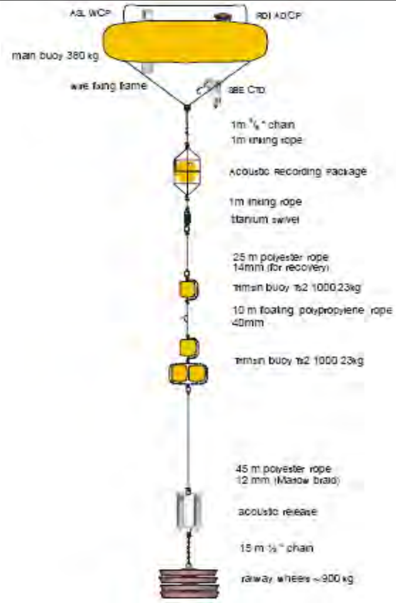
	
A) Large British Antarctic Survey (BAS) shallow water instrumented mooring with Pop-up attached to it in a cage (Source: Tanja Pangerc)	**B)** Pop-up configuration with scrap metal used as an anchor in the BRP shop (Photo by R. S. Sousa-Lima)

Figure 7. Examples of two different configurations for the same AR (Pop-up or MARU). A) Pop-up inside of a cage mounted onto a large mooring and B) Pop-up configuration with simple mooring.

Figure 8. The PAL (Passive Acoustic Listener) in a deployment case (Nystuen, 2006).

Figure 9. The EAR (Ecological Acoustic Recorder) showing 1 – the hydrophone and 2 the housing attached to a dead weight (Lammers et. al., 2008).

Figure 10. The DMON (Digital Acoustic Monitor) (DMON flyer, A. Bocconcelli, personal communication, October 17, 2009; Johnson, unpublished).

Figure 11. The AQUAclick (Retrieved from http://www.aquatecgroup.com/aquaclick.html).

Figure 12. T-POD attached to a simple mooring (Watkins & Colley, 2004).

Figure 13. C-POD (Chelonia Limited, n.d.).

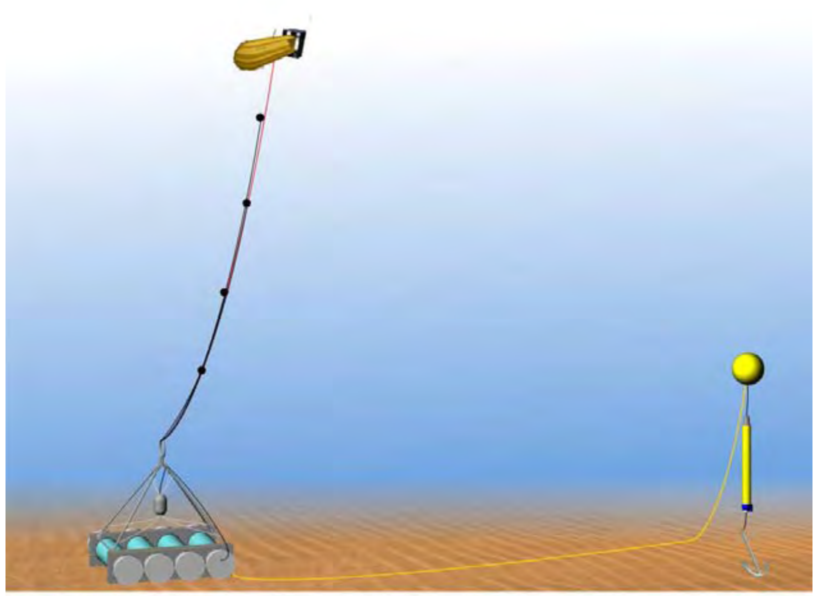


Figure 14. Directional - Vertical AMAR System with Acoustic Release. The sub-surface current sensor float suspends a vertical hydrophone array. Temperature sensors are embedded with each hydrophone to give sound speed profile measurements used for matched field processing, which is used to determine range and depth of the detected contacts. A directional sensor gives bearing (JASCO, 2009a).

Figure 15. The PANDA on deck (Koay et al., 2003)

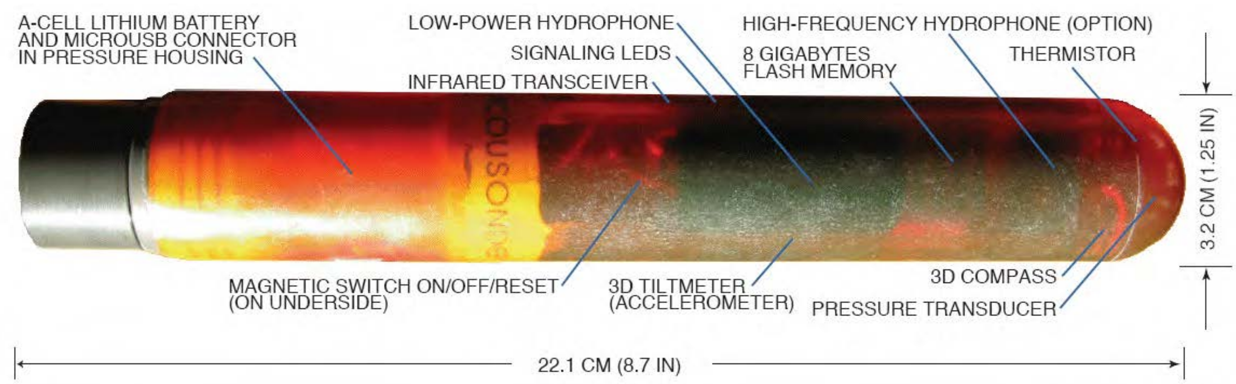


Figure 16. The Acousonde (Retrieved from http://www.acousonde.com/downloads/Acousonde_Brochure.pdf).

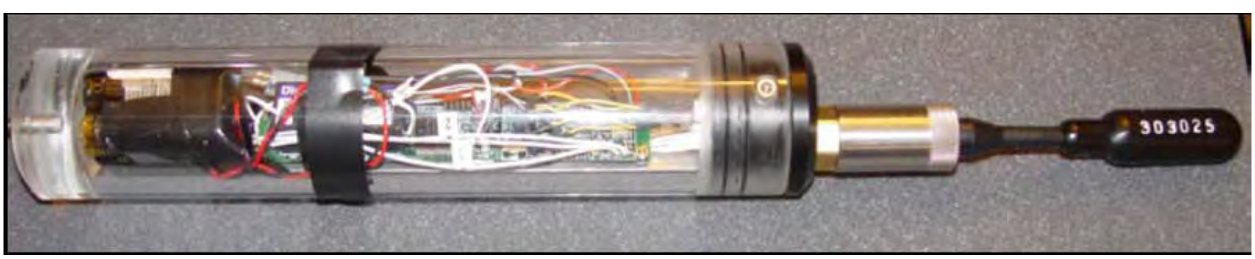


Figure 17. Autonomous Acoustic Recorder (AAR) instrument package for recording sounds, pressure, temperature, and inclination data to a 1-GB flash memory chip. The device can be powered by 4-AA batteries (Thode et al., 2006)

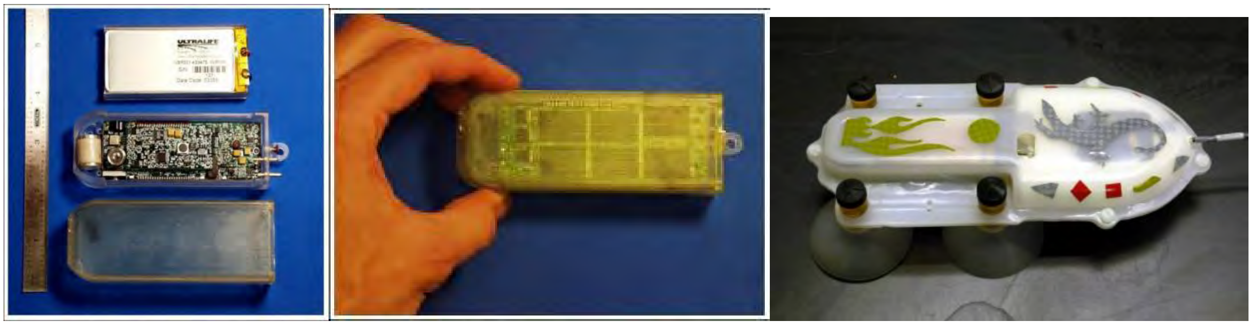


Figure 18. The DTAG components (on the left), components assembled (in the middle) and tag ready to be deployed (on the right) (Retrieved from http://www.whoi.edu/sbl/liteSite.do?articleId=27487&litesiteid=18213).

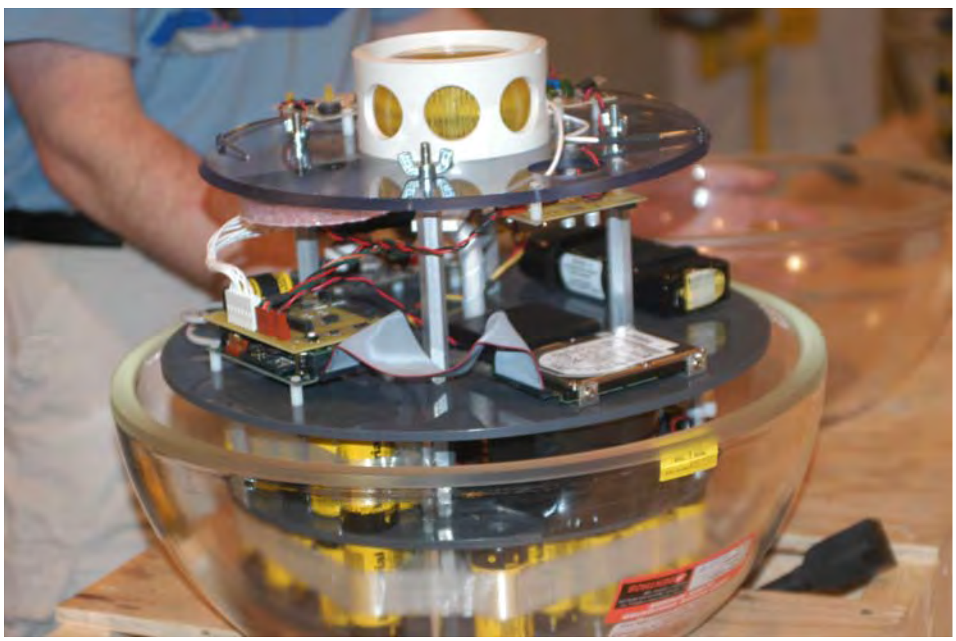


Figure 19. The pop-up is powered by a set of alkaline battery packs. The recording electronics package includes an external hydrophone (not shown here, see Figure 7), an analog amplifier, analog filter, analog to digital converter, and a hard drive for recording the collected binary audio data. The recovery system electronics includes an acoustic command recognition system, an audio signal communications system, a fail-safe time-release mechanism, a radio beacon, and a strobe light (BRP pop-up user's guide, unpublished) (Photo by R. S. Sousa-Lima).

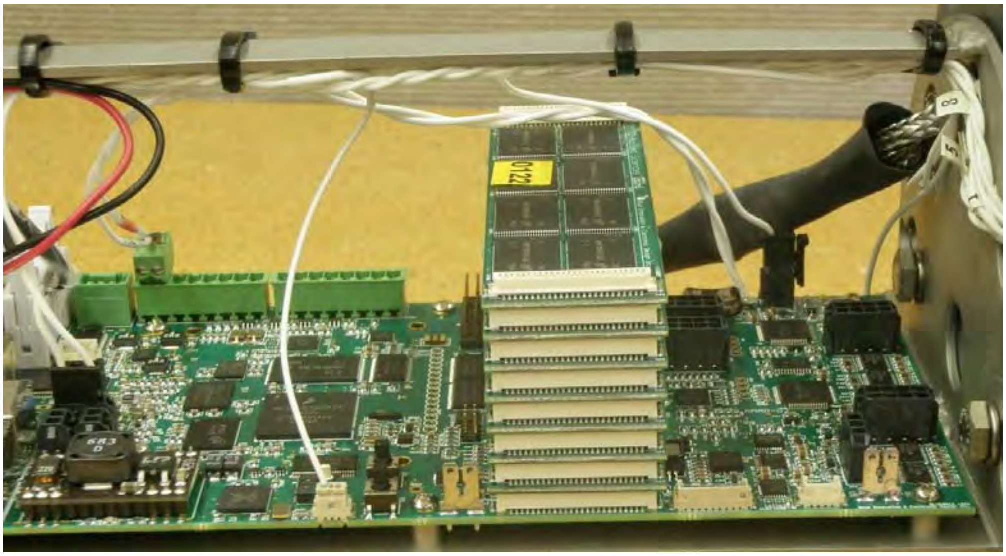


Figure 20. Close-up of an AMARS board with 1 TB of memory modules attached (JASCO, 2009b).

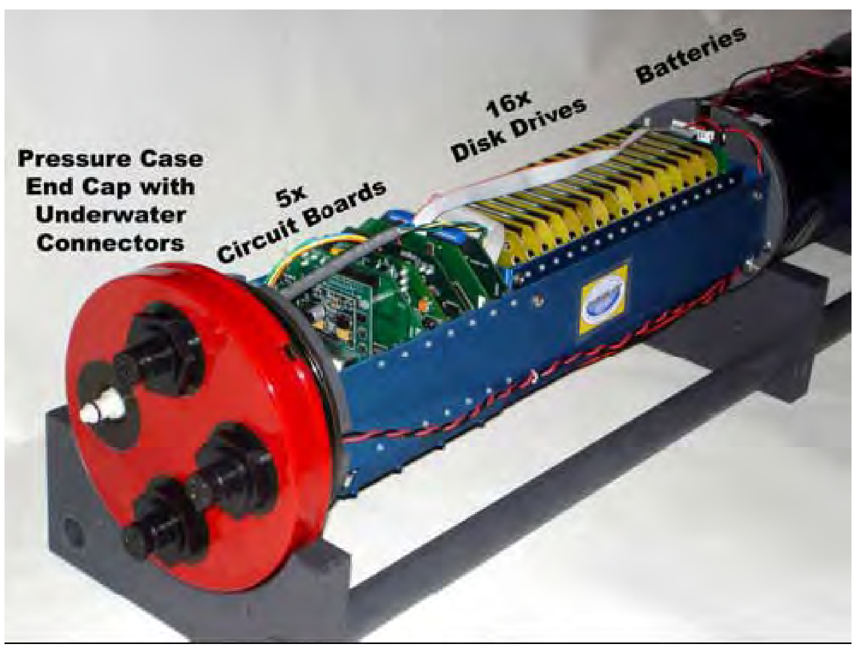
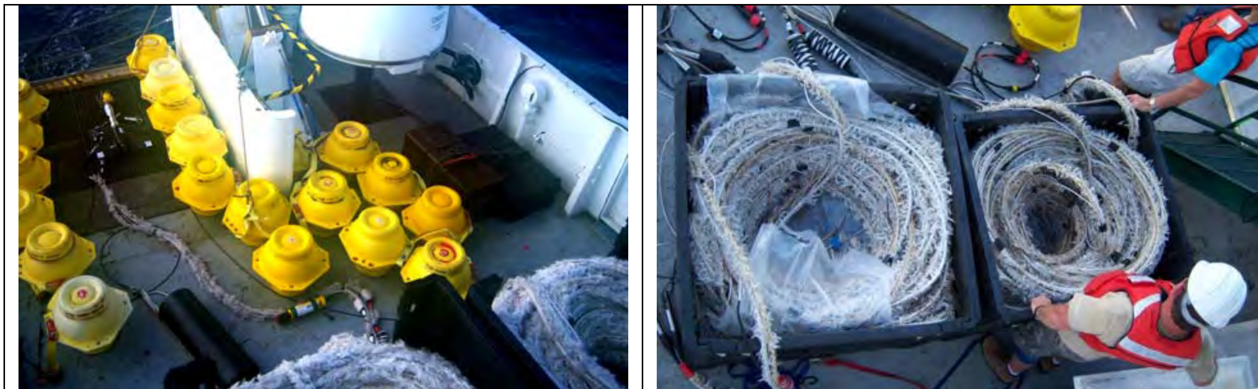


Figure 21. HARP data logger mounted on aluminum pressure case end cap (7" diameter x 2" thick) with underwater connectors. The data logger consists of a backplane populated with five primary printed circuit boards (clock, A/D, CPU, RAM, Ethernet/IDE controller), a disk block with 16 laptop computer disk drives and 48 D cell alkaline batteries. Another pressure case filled with alkaline batteries can be included for long-term deployments (Wiggins & Hildebrand, 2007).

Figure 22. The DASAR (Retrieved from http://www.greeneridge.com/technology.html).

Figure 23. EARS on deck (Photo provided by G. Ioup and J. Newcomb).



A	B

Figure 24. A) View of the EARS long mooring on deck (pre-deployment). Yellow is floatation; black cylinders are EARS buoys in frame; small yellow cylinder is USBL transponder; "winged" sensor on grate is Valeport current meter; and white-faired line is the array. B) Long arrays (300 m) in shipping boxes are deployed directly from boxes due to limited deck space. The two cylinders next to the EARS bottle are the pre-amplifiers for the hydrophones (Newcomb et al., 2009).

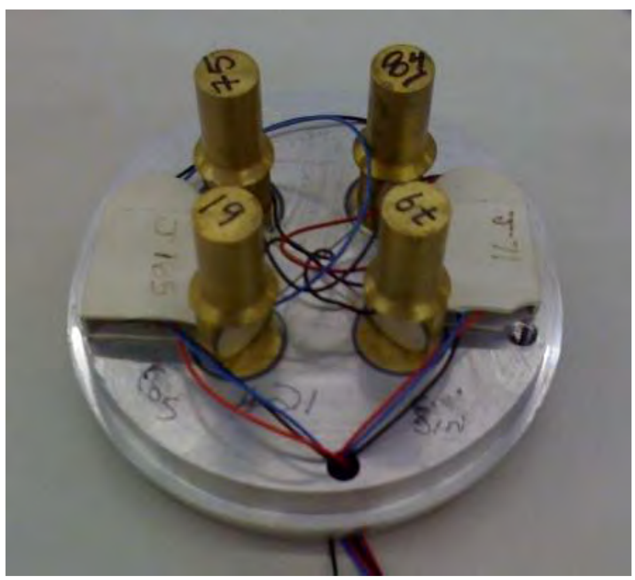


Figure 25. Particle Velocity Sensor for JASCO's directional AMAR (JASCO, 2009b).

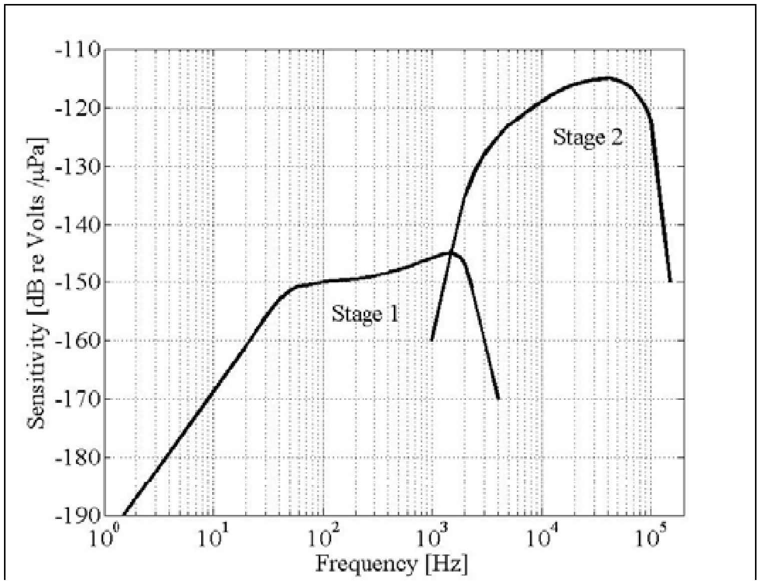


Figure 26. Hydrophone sensitivity plot showing two stages of preamplification, pre-whitening, and anti-aliasing filters. The shape of the hydrophone sensitivity was designed to follow the reciprocal of ocean ambient noise so that the sensor's response would allow for large amplitude signals across the wide band of frequencies above ambient noise (Wiggins & Hildebrand, 2007).

Figure 27. Theft of deployed PODs is a problem in some areas. One solution we have developed is the vertical grapple rig, that allows a deployment with no surface marker that can be retrieved without diving. The mooring is a weight with the POD and a line with a few small pressure-resistant floats, such as those used on the headline of gill nets to hold it up to above around half the water depth at low tide (Retrieved from http://www.chelonia.co.uk/vertical_grapple.htm, see Figure 28).

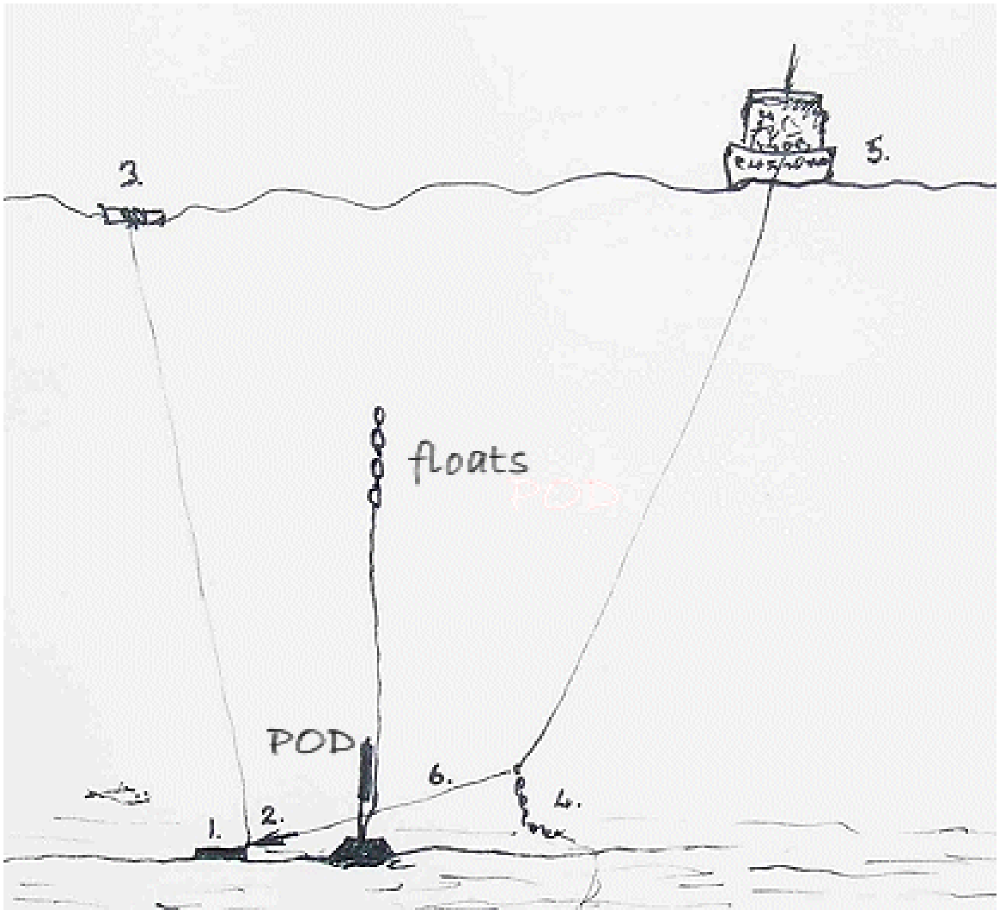


Figure 28. To retrieve the mooring a weight (1) is dropped at the position of the mooring using GPS or good sightlines. The weight (1) has a light line that is wrapped around a buoyant board (3). and this 'unrolls' as the weight sinks and stops unrolling when the weight reaches the sea bed. It then remains at the surface as a marker. The weight (1) also has a lifting/sweeper line (6) which is a stronger line and carries a length of light chain (4) which is attached at around half the water depth and keeps the line down. The line (6) has a grapple (2) in the line next to weight (1). Now the boat makes two circles around the mooring position - or around the marker (3). The rope handler tries to feel the chain (4) just touching the bottom, or tries to keep it above the ground if in a sensitive area - in which case a simple weight would be better than a chain. The boat then goes to a position above the mooring and the lifting line is hauled in. The grapple catches the vertical line with the floats and allows the whole rig to be lifted (–Retrieved from http://www.chelonia.co.uk/vertical_grapple.htm).

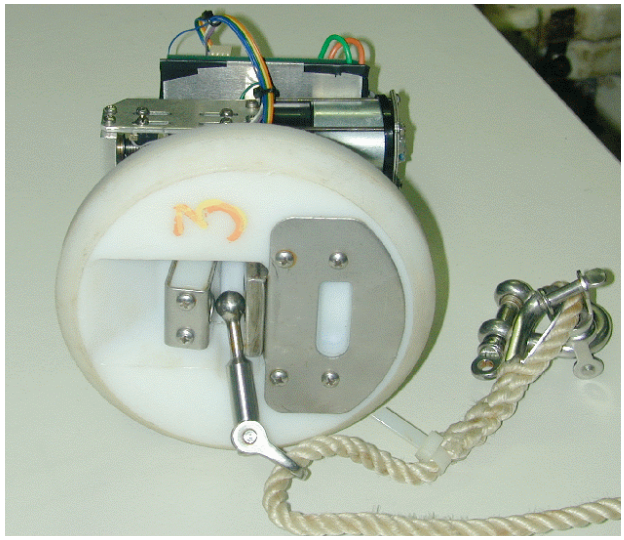


Figure 29. The PANDA Fiobuoy® Release mechanism. The recovery line is held by a retaining pin gripped in release jaws at the bottom of the instrument, leading to an anchor. When the release jaw opens (either by timed release or by acoustic command), the housing turns horizontally and ascends while unreeling the recovery line. The system is still connected to the bottom anchor. The release package has a separate, dedicated battery pack that allows the release mechanism to operate with a delay of up to one year after the main system has run out of battery (Koay et al., 2001).

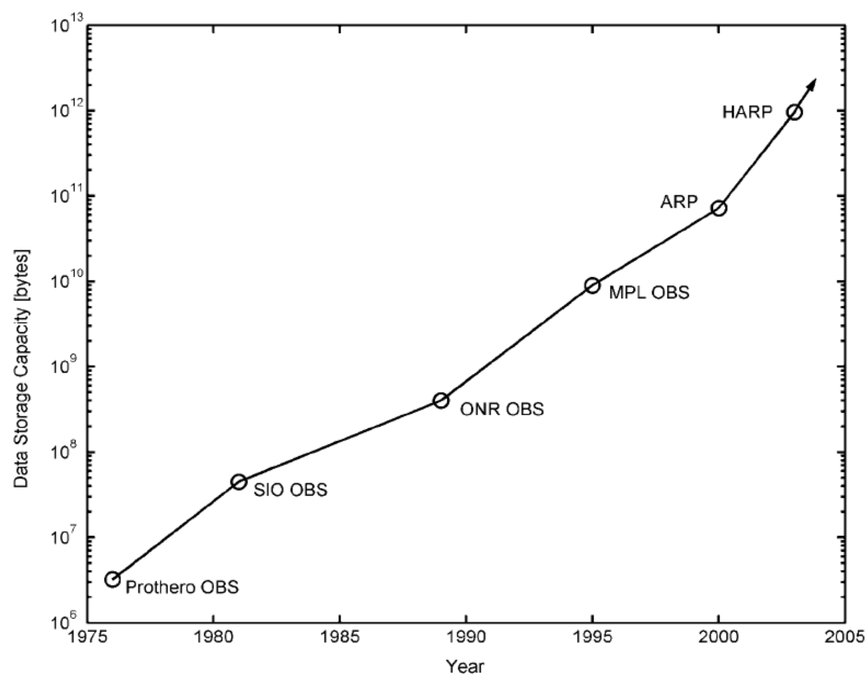


Figure 30. Storage capacity versus time for seafloor autonomous recording instruments (from Wiggins, 2003). The rate of increase in storage capacity is approximately a factor of 10 every 5 years. It is anticipated that the disk capacity increasing trend will continue for the near future (Wiggins & Hildebrand, 2007).

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A Review and Inventory of Fixed Cabled and Radio-Linked Hydrophones for Passive Acoustic Monitoring of Marine Mammals

Thomas F. Norris, Julie N. Oswald, & Renata S. Sousa-Lima

Abstract

Fixed cabled hydrophone (FCHs) and radio-linked hydrophone systems (RLHs) are permanently or semi-permanently installed acoustic monitoring systems that are located on, or moored to the seafloor. These systems have the capability to passively monitor bioacoustic signals from many species of marine mammals, and have great potential for monitoring and mitigation of potential impacts by oil and gas exploration and production, as well as other anthropogenic activities.

FCHs are powered by an external source and can send data continuously to a receiving station, usually located on shore. Examples include the U.S. Navy's low-frequency seafloor hydrophone system (SOSUS) and seafloor hydrophone arrays on test ranges (e.g. AUTEC in the Bahamas), large scale ocean observatories, small scale, deepwater neutrino observatories, 'hydrophone networks' and finally hydrophone systems designed specifically for marine mammal research.

Radio-linked hydrophone systems consist of one or more hydrophones that are moored or fixed to the seafloor and transmit acoustic signals via radio-waves to a receiving station on shore. This allows acoustic data to be remotely monitored and processed in real, or near real-time. Examples of RLHs include customized systems that have been developed to monitor large baleen whales in the shipping lanes off Boston Harbor, Massachusetts, and in heavily trafficked waterways in the St. Lawrence Marine Park, Saguenay River, Quebec. Some examples of RLH systems designed for other purposes that have been used to monitor marine mammals include the Comprehensive Test Ban Treaty Organization's International Monitoring System (CTBTO/IMS), a system of satellite linked 'hydroacoustic stations' designed for worldwide monitoring of nuclear tests.

Hybrid systems combine elements of RLHs, FCHs and autonomous recorders. They can provide real, or near real-time data acquisition greater flexibility in deployment possibilities. A few examples of hybrid systems that are undergoing development and testing are briefly discussed, with an emphasis on those that are being used, or planned to be used, to detect marine mammals.

Fixed cabled hydrophones and radio-linked hydrophone systems each have their own advantages and disadvantages. In general, installation costs are highest for FCHs, however they provide greater data bandwidth and data collection capabilities, indefinite longevity of monitoring, and

real-time capabilities. RLHs usually have lower installation costs, but their development and maintenance are usually higher than for FCHs. Hybrid systems can provide a good compromise of cost and capability, providing real-time, or near real-time, data acquisition greater flexibility in deployment possibilities but have more limited longevity and bandwidth of monitoring.

Key Words: Passive acoustic monitoring, marine mammals, cabled, radio-linked hydrophones.

1 Introduction

Fixed passive acoustic monitoring (PAM) techniques consist of hydrophones or other acoustic energy sensors that are permanently or semi-permanently fixed in location, and are used to passively collect data from various biological and non-biological sound sources. These technologies, which were originally developed in the 1950s for naval defense systems, are now well-established with proven capabilities for monitoring the marine soundscape. With recent and rapid advances in the fields of bioacoustics, digital signal processing (DSP) techniques, and micro-electronics, fixed PAM technologies have become important tools for marine mammal research, monitoring, and mitigation of human activities (Mellinger et al., 2007).

Fixed passive acoustic monitoring methods provide unrivaled capability to monitor marine mammals in remote areas, the deep ocean, and in harsh environments such as polar regions that can be difficult to access and work in using more traditional (e.g. visual) methods. In many of these environments, visual methods are expensive, ineffective, or impractical to use. Although in existence for over 50 years, fixed PAM methods, have only recently become accepted and are now commonly used to study, understand and provide solutions to important issues in marine mammal conservation and management (Barlow & Gisiner, 2006; Clark et al., 2007). The rapid advancement of computer-based DSP techniques and its application in the field of bioacoustics has resulted in an unprecedented growth in the number of permanent and semi-permanent passive acoustic systems that are now being accessed, deployed, or are planned for deployment, at numerous sites world-wide to monitor marine mammals.

In this paper, we review two main types of fixed PAM: 1) cabled systems, and; 2) radio-linked systems. Hybrids of these two technologies will also be introduced and discussed briefly where relevant for monitoring marine mammals. Although not all of the technologies reviewed here were designed or intended for uses relating to marine mammals, we have included those that are capable of, or can be easily modified for, detecting and monitoring marine mammal sounds. We provide examples of systems that are used to monitor and study marine mammals, with an emphasis on systems that have been demonstrated in field studies as being particularly effective in monitoring, tracking, and studying marine mammals in the wild. We provide basic technical information about the systems used, the species studied, and the biological questions and management issues that have been addressed using these fixed PAM technologies.

Both small scale and large scale fixed PAM systems (e.g. navy hydrophone arrays) are discussed, with a focus on systems located in or near territorial waters of the United States and Europe where most of these systems are located. Large scale systems that are in the final stages of planning or development (e.g. U.S. and E.U. ocean observatories initiatives) are reviewed, with the caveat that the designs of many of these systems are still in their planning and initial implementation stages and thus are undergoing continuous changes as the technology advances and funding issues affect plans. Finally, we provide recommendations for using fixed PAM technologies to monitor, mitigate, and investigate the effects of anthropogenic activities on marine mammals. Examples of such activities include, but are not limited to: oil and gas exploration, development, and production; naval training, testing and operational activities; ocean engineering; marine geological and oceanographic research activities (e.g. sonar and seismic surveys); boat and shipping traffic; and other human activities that produce noise and have the potential to affect the biology and behavior of marine mammals.

Cabled hydrophone systems typically consist of a long electrical cable that runs to a shore facility that provides power for the system, receives, and in some cases, transmits acoustic data to other facilities and users. Hydrophones or other acoustic sensors (e.g. seismometers) are usually located at the end of the cable. For multiple-hydrophone arrays, sensors are spliced inline on, or leading from the main cable. Due to the high costs of infrastructure required, most large-scale cabled hydrophone systems, are developed and operated by large, well-funded government and inter-governmental organizations such as national defense agencies (e.g. the U.S. Navy), national science agencies (e.g. the U.S. National Science Foundation) and international agencies (e.g. the Comprehensive Nuclear Test Ban Treaty Monitoring Organization).

Although many large cabled hydrophone systems were originally designed for purposes unrelated to marine mammals, there are numerous examples in which data collected from these systems were used to study or monitor marine mammals. Some systems, such as the U.S. Navy's SOSUS hydrophone arrays, are extensive and have been used to monitor marine mammals at ocean basin spatial scales (Nishimura & Conlon, 1994; Stafford et al., 1998; Watkins et al., 2000; Charif, et al., 2001; Mellinger & Clark, 2003). Other systems, such as deep-water neutrino detection systems were designed to detect high energy sub-atomic particles, are densely populated with hydrophones, but only cover a very small geographic region (Riccobene et al., 2009). These systems are effective for studying local populations of marine mammals in greater detail over small spatial scales (Pavan et al., 2006, 2008; Riccobene et al., 2009). Finally, there are several ongoing and planned international research initiatives to develop large-scale ocean observatories. Many of these observatories are outfitted or have plans for installing hydrophones to collect passive acoustic data (Howe & Miller, 2004; Macoun, 2007; Round, 2008).

Hydrophone 'networks' consist of individual hydrophones that are usually connected virtually via the internet. Smaller site-specific cabled hydrophone array systems have been used to study and monitor single marine mammals over small geographic areas at various locations world-wide (e.g. killer whales in Puget Sound, U.S.A., Veirs, 2004, 2008; bottlenose dolphins and harbor seals in the Beauly Firth, Scotland, Janik et al., 2000; and polar seals at the Neumayer Station Antarctica, Kindermann et al., 2008). These systems are often developed and maintained by individuals, non-profit organizations, or academic and research institutions for their respective specific research needs and other uses. In some systems, hydrophone data are available only to the researchers who developed the system, and other systems the data are streamed live via the web for direct access by scientists or the public (for examples of live data see http://orcasound.net/; PALAOA live stream).

Radio-linked hydrophone systems are those in which acoustic data are collected from a moored data-acquisition system and transmitted to shore via radio-waves. These systems are becoming more common for use in conducting marine mammal monitoring, research, and management, especially where cabled systems are not desirable or affordable (i.e. regions with strong bottom currents, heavy surf, or high likelihood of cables being fouled by fishing or other human activities). Radio-linked systems are becoming more sophisticated, reliable, and affordable as the technology matures and use becomes more widespread. Radio-linked systems are now being used for real-time detection and monitoring of endangered whales, and to mitigate vessel activity in areas with frequent ship traffic such as the Saguenay River and Boston Harbor shipping lanes (Simard et al., 2006; Clark et al., 2009). Finally, 'hybrid' technologies are being developed that combine design features of both cabled and radio-linked hydrophones with those of autonomous recorders (Matsumoto et al., 2006). These and other hybrid systems will likely become more prevalent, especially in conjunction with the large-scale ocean observatory efforts and other multi-disciplinary studies (Howe & McGinnis, 2004; Howe, 2004).

2 Cabled Hydrophones Systems

Working definition: Cabled hydrophones are permanent or semi-permanent hydrophones that are connected to a land-based receiving station (or a human-made structure) via an electrical and/or fiber-optic cable. The hydrophones are usually fixed to the ocean floor or are sometimes suspended in the water column. Acoustic data received from the hydrophone(s), or other acoustic sensor(s), are sent via the cable as analog or digital signals to the receiving station in real-time for recording, signal processing, and for archiving. Data may also be transmitted or sent (e.g. via the internet) from the receiving station, to other land-based locations to provide access by other users and systems.

2.1 A Brief History of Fixed Cabled Hydrophone Systems

Fixed cabled hydrophones have been in use since the 1950's when the US Navy decided to use this technology for detecting, locating, and monitoring noisy, diesel-powered enemy submarines in the open ocean areas surrounding the United States, Canada and the British Isles. In 1949, the Navy decided to investigate the use of passive acoustics for use in monitoring diesel submarines as part of its Anti-Submarine Warfare (ASW) effort. Dr. Hartwell, a Professor from the University of Pennsylvania formed a committee to make recommendations to the Navy (www.cus.navy.mil/timeline.htm). The Hartwell committee recommended approximately $10 million of funding per year to develop a network of bottom mounted hydrophone arrays along the continental slope of North America and the British Isles as part of a long-range acoustic detection, monitoring, and tracking system for enemy submarines and ships. 'The Hartwell Project' was a top-secret effort that marked the beginning of a new era of passive acoustic monitoring of the worlds oceans and continues today in various forms with a variety of defense, scientific and socio-political objectives.

2.1.1 The U.S. Navy's Hydrophone Array Systems

In the early 1950's the U.S. Navy began installing the large-scale system of underwater hydrophone arrays at key strategic locations in the United States, the Caribbean Islands, Canada, and later, in Northern Europe. The hydrophones were typically located on the continental slope so that they could 'look' into deep waters for ships and submarines entering waters off the U.S. and UK. In 1951, a secret test array, known under the project name 'Jezebel', was installed off of Eleuthera Island in the Bahamas. The following year, the Sound Surveillance System (SOSUS) was officially initiated with the installation of a large, 40-element low-frequency hydrophone in a water depth of just over 100 m array off Eleuthera Island (Whitman, 2005).

SOSUS was designed to detect and monitor noisy, diesel powered submarines, at great distances. A Low-Frequency Analyzer and Recorder (LOFAR) processing system, based originally on a human speech spectrographic analyzing machine (originally developed by AT&T) was used to process the acoustic signals received from SOSUS (Whitman, 2005). This system relied on human operators who constantly monitored spectrograms to detect signals of interest in the 25 200 Hz low frequency band. This band contained the peak frequencies produced by the machinery and propellers of most submarines, but also contained calls from whales. Beamforming methods were used to process the acoustic data so that the positions of submarines could be determined via triangulation of beams received from multiple hydrophone arrays (IUSS, 2009).

During the ten year period between 1951 and 1960, over 20 cabled SOSUS arrays and receiving stations (called 'NAVFACs') were established at various locations off the west and east coasts of the U.S. as well as the Bahamas, Puerto Rico, and other Caribbean Islands, Newfoundland and Nova Scotia, Canada. Between 1961 and 1985, an additional 20 or so arrays and receiving shore stations were established in areas as wide-ranging as Iceland, the British Isles, Guam, Midway Island, and Adak Island, Alaska. Most of these systems remained operational until the end of the cold-war era when they became obsolete due to noise-reduction technologies that were developed to quiet submarine propulsion systems during this time period. Beginning in 1970, the first receiving station (at San Salvador Island in the Caribbean Sea) was 'de-established.' Over the next 30 years almost all of the remaining NAVFAC shore receiving stations were de-established (IUSS, 2009).

In the mid-to-late 1980s, signals received from the few remaining SOSUS arrays were consolidated by routing them to a few centralized receiving stations called Naval Ocean Processing Facilities (NOPF). In the U.S., there were two NOPF stations: one was located on the U.S. west coast at Whidbey Island, WA, and the other on the U.S. east coast at Dam Neck, VA. Additional stations were located in Canada and the U.K. (IUSS, 2009). The remaining SOSUS arrays, and data that they produced, were integrated into what is now called the Integrated Undersea Surveillance System (IUSS) program which still continues to operate today (Whitman, 2005). Cables from most of the 'de-established' SOSUS hydrophone arrays were presumably cut, destroyed, or otherwise disabled to prevent unauthorized access to the acoustic signals. The exact location and operational status of most of these cables remain classified. A few of the original SOSUS arrays (e.g. the Pt. Sur, CA array and the Barber Pt. HI array) were briefly taken over by research institutes for collecting acoustic data for scientific research (Orcutt et al., 2000), however most of the de-established SOSUS arrays remain non-operational today.

2.1.2 Marine Mammal Research Using SOSUS and IUSS

Since 1995, the remaining operational IUSS systems have been occasionally used for bio-acoustic research, primarily to monitor and track several species of baleen whale such as blue, fin, humpback and minke whales (Nishimura & Conlon, 1994; Moore et al., 1999; Mellinger et al., 2000; Mellinger & Clark, 2003; Watkins et al., 2000; Charif et al., 2001; Stafford et al., 1998; 2001; Andrew et al., 2002a; Andrew 2002b). All of these species produce sounds that consist of, or include low-frequency components that are easily detectable with SOSUS hydrophones. Although there once were high hopes among scientists that these monitoring facilities would become an important asset to the research community at large, access to these classified facilities and data, to this day, remains limited to a few researchers with the necessary security clearances and U.S. Navy connections. Furthermore, data classification issues have limited the types and availability of information that can be used in scientific reports and publications which can be problematic for the peer review process required by most scientific journals.

Between 1993 and 2001, the Naval Postgraduate School (NPS) in Monterey, CA acquired a decommissioned SOSUS array off of Pt. Sur and operated it as part of their Ocean Acoustic Observatory (NPS, 2009). This hydrophone array has been used to conduct various NPS led studies on blue whales acoustics (Chiu et al., 1999; Kumar et al., 2002, Kumar, 2003). Studies of man-made natural ambient noise collected using the Pt. Sur array also have been conducted. For example, a long-term study of ambient noise from whales and vessel traffic using data collected in 1960s from this observatory was compared to data collected from the same receiver in the 1990s (Andrew et al., 2002a, 2002b). Increases of 3 and 10 dB in the 8-20 Hz band and 200-300 Hz band, respectively, were discovered. These changes were attributed mostly to increases in (distant) shipping traffic, with a 3 dB or less increase attributed to blue and fin whales sounds occurring below 30 Hz.

2.1.3 U.S. Navy Acoustic Test Facilities (AUTEC / SCORE / PMRF)

More recently, hydrophone arrays from the U.S. Navy experimental and test facilities such as the Atlantic Undersea Test and Evaluation Center (AUTEC) range in the Bahamas, the Southern California Offshore Range (SCORE) and the Pacific Missile Range Facility (PMRF) in Hawaii have been used to detect, monitor, and even passively track cetaceans using the sounds they produce (Morretti et al., 2006; DiMarzio & Morretti, 2008; Marques et al., 2009). These Navy systems and related research efforts are being reviewed by others in a related OGP/JIP effort and will not be discussed further here.

2.2 Opportunistic Studies of Marine Mammals using Cabled Hydrophones

There are many cases of single fixed hydrophones that have been used for monitoring calls of marine mammals, or have incidentally recorded sounds produced by marine mammals. Only a few important examples of these are provided below because the details and current status of many of these are not published or readily available.

As early as 1958, calls from whales were recorded on hydrophones, usually deployed by national defense agencies, at various sites around the world. In many of these early studies, there were many sounds that considered to be produced by biological sources. Many of these biological sounds were suspected to be produced by marine mammals, however, the species identity usually could not be confirmed, (Walker, 1963; Kibblewhite et al., 1967). In the winters of 1965 and 1967, researchers working on U.S. Navy sponsored research projects recorded low frequency (~ 20 Hz) sounds of unknown, but suspected biological origin (Northrup et al. 1968; Northrup et al., 1971) at several sites in the central Pacific Ocean (e.g. the Pacific Islands of Kauai, Eniwetok, Midway, Wake, and Oahu Islands). The latter recordings were made from three U.S. Navy hydrophones located in the SOFAR channel on a seamount near Midway. These sounds are now known to be produced by blue whales (McDonald et al., 2006).

Thompson & Friedl (1982) conducted a long-term study of low frequency sounds of several species of whales recorded from two bottom mounted hydrophones located 11.6 km apart and a water depth of about 800m off Kahuku point, on Oahu, Hawaii. These hydrophones were part of a Navy underwater monitoring system. They were able to detect fin, humpback, blue, pilot and sperm whales, as well as sounds they called 'boings' that now are known to be produced by minke whales (Rankin & Barlow, 2005). Analysis of the relative occurrence of these sounds showed strong seasonal peaks for some species (e.g. humpback and minke whales) and lower peaks for others (e.g. sperm and pilot whales; Thompson & Friedl, 1982).

About twenty years later, McDonald & Fox (1999) analyzed acoustic data from one of the same two hydrophones north of Oahu used in the Thompson & Friedl (1982) study to investigate the possibility of estimating densities of fin whales north of Oahu. They proposed a technique for determining minimum density estimates, however, there were some important study design and statistical issues that remained unresolved. In another, unrelated study, McDonald (2006) analyzed data recorded from a pair of hydrophones 5 km east of Great Barrier Island, New Zealand. The data collected from these hydrophones were being used to evaluate the possibility of monitoring nuclear explosions as part of the Nuclear Test Ban Treaty Monitoring effort (reviewed in detail later). Seasonality and songs were examined for several species of baleen whales. Song types for blue and humpback whales were characterized, as were calls from fin and Bryde's whales.

2.3 Dedicated Cabled Hydrophone Systems for Marine Mammal Research

Few cabled hydrophone systems have been designed and used specifically for marine mammal research. Relative to the Navy's SOSUS arrays, these are much smaller systems, both spatially and with fewer operations and maintenance requirements. Most of these efforts have been funded through small research organizations, academic institutions, or by small non-governmental and non-profit groups.

The first fixed cabled hydrophone array system dedicated to monitoring marine mammals was developed in the late 1970s to study a population of southern right whales (*Eubalaena australis*) in Golfo San Jose, Argentina (Clark & Clark, 1980). This semi-permanent system consisted of three hydrophones arranged in a small (1.5 m vertice) triangle in relatively shallow water depths (<12 m). The digital processing system associated with this system used phase differences in signals received at the three hydrophones to estimate the direction of sounds produced by whales inside the bay. This system was used to collect hundreds of hours of whale calls that were then correlated with behaviors and movements of animals visually monitored from a cliff-top look-out (Clark & Clark, 1980; Clark, 1983).

Janik et al. (2000) developed a 3 element array that was used to study harbor seals *(Phoca vitulina)* and bottlenose dolphins *(Tursiops truncatus)* in a shallow 500 m wide channel in the Beauly Firth in Scotland, U.K. The hydrophones were configured in a triangular pattern with two of them located on one side of the channel and the third located on the opposite side of the channel. This configuration allowed calls from animals to be unambiguously triangulated using time-differences of arrivals computed using spectrogram cross-correlation. This system is still operational (Janik, 2009, pers. comm.).

The Puget Sound area of the Pacific Northwest U.S. and Canada has several cabled single hydrophones and small hydrophone arrays. A network of hydrophones installed and maintained by a coalition of scientists, educators, and citizens called the 'Salish Sea Hydrophone Network' is accessible via the internet (http://orcasound.net/). This network was intended primarily to allow interested parties and the general public to monitor and/or track general movements of resident killer whale pods and to communicate about their whereabouts and activities by posting messages via an email list, text messaging, and the posting of recordings on the website.

A relatively sophisticated hydrophone array system that is also part of the Salish Sea Hydrophone Network is the Orcasound hydrophone array, developed and operated by Dr. Val

Veirs of BeamReach, a marine science educational program. The array is located just off Friday Harbor Island (U.S.), and consists of 4-8 hydrophones distributed along a 200 m path parallel to the shore at water depths of 5-20 m. The system is mounted on tripods 1-2 m above a gravel bottom. The cables traverse the rocky inter-tidal zone to a shore station with a computer for data-logging and live streaming to a website. Custom-developed software calculates average sound levels for underwater ambient noise and automatically detects killer whale calls and man-made sounds such as navy sonar signals (Veirs, 2008)

3. Radio-Linked Hydrophone Systems

Working Definition: Radio-linked fixed hydrophones consist of a hydrophone that is moored, tethered, suspended or fixed to the seafloor. Free drifting hydrophones such as sonobuoys[1] are intentionally not included as part of this definition, as typically they are not fixed and are used for short term (< 8 hr) deployments. Acoustic data from radio-linked hydrophone are usually transmitted to a receiver or receiving station in real-time via radio signals (usually VHF transmitter, satellite or cellular-phone networks). In some cases data are preprocessed before they are sent to a receiving station.

3.1 A Brief History

The first radio-linked oceanographic buoy was developed by the renowned oceanographer, Henry Stommel in the early 1950s (Stommel, 1954). Stommel's oceanographic buoy consisted of a wind anemometer, a temperature sensor, and a radio transmitter to telemeter data from the buoy to shore or a ship and was designed by a team of engineers and scientist from Woods Hole Oceanographic Institution (WHOI).

Fixed radio-linked hydrophone systems have been used to study whales since the mid 1980s, and continue to be used today. Typically these are semi-permanent systems that can

[1] Sonobuoys are expendable passive acoustic monitoring devices used by navies to detect submarines and other motorized vessels. They consist of a hydrophone, a VHF transmitter and some circuitry that allows certain settings to be user controlled before deployment. They are free-floating devices that automatically scuttle after a user-selected time period of 8 hours or less.

require considerable maintenance, such as battery replacement, and replacement of failed, flooded or corroded electronic equipment. Many of these early systems used VHF radio for acoustic data-telemetry and are modeled after (or modified directly from) sonobuoy systems (Hunter & Morris, 1987; Van Parijs, et al., 1998; Gedamke, 2004). Sonobuoys are expendable, freely-drifting instruments that typically are used for short-term or temporary deployments (< 8 hrs) (e.g. Laurinolli et al., 2003). Sonobuoys have been used to study marine mammals since the 1970s (Levenson & Leapley, 1978). However, they do not meet our working definition of a fixed PAM system and therefore will not be discussed further.

More recently, cell phone and satellite communication technologies have been used to transmit data in real or near-real-time, or more commonly, to transmit processed data or data summaries to a shore-based station (Simard et al., 2006, Matsumoto et al., 2006; Spaulding et al., 2009; Clark et al., 2007; 2009). Once the data are received on shore, the internet is often used to provide real-time (i.e. streaming) data links for data distribution and dissemination to the public (Kindermann et al., 2008).

3.2 Review of Radio-linked Hydrophone Systems

Radio-linked arrays have been used primarily to study baleen whales occurring in nearshore environments. This is probably due to technological constraints of limited bandwidth (usually < 20 kHz) and limited line-of-sight (or cellular tower coverage) of radio transmission ranges. Satellite-linked systems can overcome limitations in transmission range but suffer from limited bandwidth and costly service and data-transmission fees. For VHF radio systems, receiving antennas mounted on elevated shore-stations can significantly increase radio reception distances, especially in areas with high relief. Many early systems were based on, or utilized modified sonobuoy technology. For example, Cummings and Holliday (1985) used a modified sonobuoy[2] array fixed to the ice to census bowhead whales (*Balaena mysticetus*) off Pt. Barrow, Alaska. Clark et al. (1986a, 1986b) used a similar system to locate and track whales at distances of 3-4 times the baseline length of the array along ice leads in the same general area (Clark & Ellison, 1988, 2000).

[2].Modifications to sonobuoys for research usually involve disabling the scuttle mechanism and in some cases modifying or supplementing the battery power supply to extend their operating lifetime.

3.2.1 Overview of Radio-Linked Hydrophone Systems

Whales wintering and migrating through sub-tropical areas such as the Hawaiian Islands and Australia have been studied using similar VHF radio-linked systems. Frankel et al. (1995) developed a semi-permanent radio-linked hydrophone array moored to the seafloor to track movements and behaviors of singing humpback whales (*Megaptera novaengliae*) off the main island of Hawaii. More recently, there have been several similar efforts to study humpback whales off the eastern coast of Australia (Dunlop et al., 2008; Noad & Cato, 2007; Noad et al., 2004). Gedamke (2004) used modified sonobuoys to develop a semi-permanent, five-element array that was used to localize and track movements of singing minke whales over a 100 km area in the Great Barrier Reef, Australia. Most of these studies combined radio-linked hydrophone methods with visual monitoring and tracking, in order to provide a more complete picture of animal locations, movements, and behaviors.

All of these systems relied on VHF radio-transmitters to transmit signals ashore, usually across relatively short distances (< 10 km). The nature of VHF signals requires placement of transmitting and/or receiving antennas at suitable heights within a direct line-of-sight path, to achieve usable transmission distances. Other technological and regulatory issues that can affect the performance of these systems include the power of radio transmissions and the choice of radio frequency (both of which are tightly regulated by the Federal Communications in the U.S. and by a variety of agencies in Europe). Additionally, antenna design and receiver characteristics can significantly affect the range and quality of signals received.

Finally, there are significant maintenance issues. VHF telemetry systems typically are powered by DC batteries, which in most cases are located close to the radio-transmitter. Typically, a water-tight container housing the electronics is attached inside or on-top of a buoy for this purpose (Van Parijs et al., 1998). Unless recharged via solar, wind or other sources, the batteries must occasionally be replaced. The hydrophone is attached to the electronics package via a waterproof cable with the hydrophone suspended just above, or fixed to, the seafloor. The buoy must be secured to the seafloor using anchors or moorings. As with any anchored system with a surface buoy, they are susceptible to currents, seas, swell and in some areas, theft, vandalism, and interactions with fisheries and other human activities.

Recently, more sophisticated radio, cell-phone and satellite-linked buoys have been developed and deployed to monitor a variety of large species of whales. For example, relatively sophisticated systems were developed to monitor the effects of shipping on blue whales in the Saguenay-St. Lawrence Marine Park, Canada (Simard et al., 2006; 2008a; 2008b) and right whales in shipping lanes just off Boston Harbor (WHOI News Release, 2008).

The system in the Saguenay-St. Lawrence Marine Park was developed by a collaborative team of scientists from the University of Québec and the Department of Fisheries and Oceans Canada (DFO). This system consisted of a satellite linked acoustic buoy capable of real-time, 2-way data transmission via 900 MHz radio transmitters and an Iridium satellite modem (Simard et al., 2006). This system was capable of storing up to 100 GB of data. The total storage capacity was expandable with the addition of more hard drives. The acoustic data acquisition was capable of sampling up to 16 (or 8 differential) analog channels at speeds of up to 500 Hz. RF communication is accomplished via a 900 MHz modem connected to an onboard PC. Data transfer rates were user definable from 10 to 120 Kb/sec.

The system developed by Simard et al. (2006) uses a 2 m antenna is that is mounted approximately 2 m above the waterline. The maximum range of transmission is rated at 64 km. Two-way communications are provided via an Iridium satellite modem which can communicate at a rate of 2.4 Kb/sec. Both the satellite and the RF antennas are mounted on the top of the buoy on a gimbal to reduce the swaying motion from waves and tidal currents. The buoy (0.8 x 1.1m) is moored to the seafloor. A reliable mooring method was needed because the study area is a tidally influenced river-estuary that is exposed to extremely strong currents. Their system is also capable of automated call detection via an onboard computer and detection algorithms. Call detection and localization are performed within a 'master' buoy that receives data from the other buoys. The detection algorithms can be configured so that they are able to detect vocalizations from other species as well.

Another automated whale detection system was recently developed by researchers at Cornell University's Bioacoustics Research Program (BRP) and the Woods Hole Oceanographic Institution (WHOI news release, 2007; Cornell Lab of Ornithology press Release, 2008). This system was designed to provide near real-time information regarding the presence of right whales to the captains of large vessels (such as LNG tankers) navigating shipping lanes off of Boston Harbor so that collisions with animals may be avoided (Figure 1). Each 'whale auto-detection buoy' is instrumented with a hydrophone and an electronics package to control the system and process acoustic data. A flexible cable that was specially designed with data-transmission wires woven into its walls and is capable of stretching to twice its normal length was developed for this system. A special mooring design was also developed that allows the buoys to withstand the often hostile sea conditions in the shipping lanes off of Boston Harbor, where the system is deployed. Data from the hydrophones are processed by a computer system located in the surface buoy (Spaulding et al., 2009). This system continuously analyzes incoming acoustic data and automatically detects potential right whale calls. Satellite and cellular communication links are used to send saved acoustic detections and associated metadata every 20 minutes to an acoustics lab at Cornell University, in Ithaca, NY. These data can then be reviewed by experienced bio-acoustics technicians. The technicians decide whether the signals are from right whales, and if so, this information is used to alert ships of the presence of whales in the area via a maritime telecommunications network.

3.2.2 Comprehensive Nuclear Test Ban Treaty Organization's International Monitoring System- The International Monitoring System (IMS) is a worldwide network of sensors and monitoring instruments that is used to monitor the occurrence of nuclear explosions from countries conducting nuclear weapons tests. It is funded and managed under the auspices of the Comprehensive Nuclear Test Ban Treaty Organization (CTBTO) located in Vienna, Austria. The IMS is responsible for developing, maintaining, and operating a network of 'hydroacoustic stations' which include both hydrophones and/or seismometers (Hanson et al., 2001). Eleven stations are located at various sites worldwide (Figure 2). Five of these stations include hydrophones and are located at mid-oceanic islands in the Pacific, Atlantic, and Indian Oceans, with one station located off Cape Leeuwin, Western Australia. Four newly designed and developed stations that included hydrophones were used to supplement two existing hydrophone arrays that were taken over from the U.S. SOSUS program (Forbes et al., 2006).

The hydrophone arrays for the new stations are connected to shore via fiber-optic cables. In each of these installations three low frequency (1-100 Hz +/- 1 dB) omni-directional hydrophones are installed in an equilateral triangle configuration. For island stations, two arrays were installed, one each on opposing sides of the island in order to minimize the sound shadowing effects caused by 'island blockage'. The hydrophones are buoyed from the seafloor at depths that corresponds to the axis of the SOFAR channel (Forbes et al., 2006).

Data are stored at each station in a temporary seven day buffer that serves as a short-term emergency backup in case of communication or power outages (Lawrence & Grenard, 1998). Acoustic data from these stations are then transmitted via a two-way satellite communication terminal to the CTBTO International Data Center headquarters in Vienna, Austria for processing and long-term archiving.

Data from CTBTO/IMS hydrophones have been used to study blue whale calls from hydrophone stations off the coast of Possession Island (French Territory) part of the Crozet Archipelago in the southwest Indian Ocean (Samaran et al., 2008) and from Cape Leeuwin, Western Australia (Gedamke et al., 2007). Because of the limited bandwidth (below 100 Hz) for CTBTO acoustic data, only low-frequency calls from the largest species of baleen whales, such as blue and fin whales can be reliably detected. Samaran et al. (2006) analyzed one year of data from a CTBTO/IMS hydroacoustic station from Possession Island. They detected and identified calls from two blue whale subspecies (the Antarctic/true blue whale type, *Balaenopetra musculus intermedia*, and the Madagascar type pygmy blue whale *B. m. brevicauda*). They also identified the calls of fin whales (*B. physalus*). Blue whale movements were examined using time differences of arrival when animals occurred near the hydrophones (Samaran et al., 2008). Animal ranges from the hydrophones were estimated to be up to 50 km. Distinct seasonal patterns in relative call occurrences were also detected.

McDonald (2006) used archived data collected in 1997 from a pair of seafloor hydrophones that were evaluated as a potential site for an IMS hydroacoustic station off of the Great Barrier Island, New Zealand. These included numerous occurrences of Bryde's whale calls, and blue, fin, humpback whale songs. In McDonald's study spectrograms were manually examined for whale calls and songs. The goals of this study were to examine seasonality of whale sounds and provide rudimentary estimates of densities of calling animals.

In a study by Gedamke et al. (2007), data from a single hydrophone of the CTBTO array off Cape Leeuwin, Western Australia were collected for a 3 year period between January 2004 and April 2007. These data were sampled at a rate of 250 Hz providing an effective bandwidth of ~100 Hz. A long-time series Power Spectral Density (PSD) analysis was performed on these data to provide information on seasonal energy in the frequency bands in which blue and fin whale calls occur (Figure 3). Calls from the Western Australian and Antarctic Blue whale populations were clearly evident as were calls from fin whales.

A commercially available radio-linked hydrophone systems developed by Seiche Monitoring Ltd.'s Passive Acoustic Monitoring Buoy has been used to conduct real-time monitoring near well heads undergoing decommissioning in the North Sea (Pierpoint & Gill, 2005). This buoy-based hydrophone array is designed to be semi-permanently moored for remote monitoring of marine mammal and other sounds. The radio-linked hydrophone system utilizes a buoy platform to mount two vertical hydrophone arrays which are suspended below the buoy. Six channels of data in the frequency band of 2 kHz to 200 kHz can be processed in the buoy and transmitted via a radio link to a monitoring vessel or base station. The received audio signals can then be processed using standard mammal processing and monitoring software (e.g. *Rainbow click/logger* or *PAMGUARD*). The buoy's power system can be controlled remotely enabling the battery life to be conserved when monitoring is not required

3.3 Hybrid Systems

A 'hybrid' passive acoustic device called the QUEphone (Quasi-Eulerian hydrophone) is currently being developed by Oregon State University and NOAA's Pacific Marine Environmental Laboratory (Matsumoto et al., 2006). It is essentially an autonomous recording and processing system with an integrated hydrophone, satellite modem, and GPS receiver. The QUEphone is a free-floating, autonomous recorder that can maintain a relatively fixed position in the ocean (depending on ocean currents) but does not require a mooring. Upon deployment it dives and remains at depth until the detection of an acoustic event such as a sudden increase in seismic activity or calls of marine mammals, whereby it ascends to the surface. Once at the surface, the QUEphone transmits small data-files via satellite to shore so that the data can be examined in near real-time by scientists.

The QUEphone includes a data-processor that runs automated algorithms for detecting specific types of sounds. The onboard GPS is used for clock synchronization and to provide instrument location information that is included in the data files sent ashore. The data-transmission rate is 2.4 k-bits/sec., enough to send a file of about 1000 low frequency seismic events (Matsumoto et al., 2006). The current design is rated for 2000 m depths and is automatically programmed to limit dive depth of the device to less than this so as to prevent damage. The *QUEphone* prototype has been successfully tested to descend, record sounds and ascend, but the real-time detection and response feature has not yet been fully tested *(*Mellinger*, 2009 pers.* comm.; Matsumoto et al., 2010).

There are various other hybrid systems under development, such as gliders and autonomous vehicles that include integrated passive acoustic monitoring systems, many of which are capable, or already being used to detect marine mammals. These new technologies will undoubtedly become important for monitoring marine mammals in the near future. Because these systems do not meet our definition of 'fixed', they will not be reviewed here. However they should be considered as viable technologies for monitoring marine mammals.

4 Ocean Observatories

Working definitions:
Seafloor ocean observatories consist of bottom mounted or moored sensors and instruments deployed permanently or semi-permanently on the seafloor. Typically, a variety of instrumentation and sensor packages (that may include hydrophones) are used in ocean observatories. Ocean observatories may consist of cabled or radio-linked instruments or some combination of these. There are many varieties of ocean observatories; however this review will focus primarily on the following two categories:

1) Acoustic ocean observatories are permanent or semi-permanent systems with the primary purpose of passive acoustic data collection and monitoring via hydrophones or other acoustic sensors. For some observatories (e.g. ATOC/NPAL), sound sources are included as part of the system.

2) Cabled ocean observatories (also called permanent seafloor observatories) are ocean observatory systems that consist of an undersea cable connecting the hydrophones and other instrumentation on the seafloor to a shore-station which provides power and communications capabilities. The more recently developed observatories have a networked infrastructure that utilizes junction boxes (called nodes) to allow a variety of platform independent instruments to be easily attached and detached as needed for maintenance, repair or just to change instrument packages. Electrical and fiber-optic cables are used to provide power and communications over the great distances (>100 km) of the observation network. In this review, we will focus on cabled observatories with existing, planned, or potential connectivity to hydrophones..

4.1 Brief History of Ocean Observatories with Passive Acoustic Sensors

Henry Stommel, the late renowned oceanographer, was the first to propose a permanent, 'oceanographic observatory.' He proposed a system off Bermuda using radio-linked oceanographic buoys (as described earlier in this review; Stommel, 1954). Unfortunately this visionary project was eventually abandoned by its sponsors before it could be fully demonstrated (Carlowicz, 2008).

The first cabled hydrophone array system designed exclusively for marine bio-acoustic research was developed in the Bahamas in the early 1960s (Steinberg et al., 1962). This visionary ocean observatory effort was constructed in shallow waters off of the now defunct Lerner Marine Laboratory on North Bimini Island in the Bahamas. The hydrophone array and other instrumentation for this observatory were located off the western edge of Great Bahama Bank. This project was funded primarily by the U.S. Office of Naval Research, but included a team of academic, military and private researchers and engineers (Kroendiger et al., 1964). The primary purpose of this experimental facility was to study the feasibility of using permanent hydrophones to monitor and observe 'soniferous marine animals' in their natural environment (Steinberg et al., 1962).

The system was used over a two year period to record and study a variety of acoustically active marine organisms including cetaceans. Recordings were made on reel-to-reel magnetic tape and post-processed by a team of scientists and technicians who characterized biological sounds and assessed the identity of their sources (Cummings et al., 1964). This multi-instrument system included an underwater sound projector, a bait trap, and a video camera to monitor reactions of marine life to sound playbacks (Kroendiger et al., 1964). This was a relatively advanced and pioneering acoustic-visual underwater observatory for its time, predating present day ocean observatory systems by over 40 years.

4.2 Ocean Observatory Programs, Initiatives and Organizations

The Global Ocean Observing System (GOOS) is the oceanographic component of the Global Earth Observing System of Systems (GEOSS). GEOOS is a system of research programs that provides monitoring of the present state of the oceans, including living resources; forecasts of sea conditions and data collection for forecasts of climate change. GOOS is a permanent global system for observations, modeling and analysis of marine environmental variables. The purpose of GOOS is to establish ocean observation capabilities worldwide. It is being implemented by its member states via their respective government agencies, navies and oceanographic research institutions. Currently, over 30 nations conduct activities as a part of GOOS, with contributions from national agencies, private institutions, and individual oceanographers. The member nations perform a wide range of tasks in support of the GOOS effort, including the installation and maintenance of *in situ* observing networks, launching of ocean satellites, maintenance of real-time data streams and data archives, and the ocean information and forecast products. GOOS is sponsored by the United Nations and the United Nations Environment Programme (UNEP) as well as the Intergovernmental Oceanographic Organization (IOC), the World Meterological Organization (WMO) and the International Council for Science (ICSU).

4.2.1 Ocean Observatory Initiatives in the U.S.A & Canada

The Integrated Ocean Observing System (IOOS) is a multidisciplinary 'system of systems' and network of people and technology that generates and disseminates continuous data on coastal waters and oceans in the United States. IOOS represents a national partnership among 17 Federal agencies and 11 Regional Associations that share responsibility for the design, development, operation, and maintenance of a national network of ocean observatories.

The National Oceanic and Atmospheric Administration (NOAA) and its partner agencies and organizations have participated in the development of the IOOS since its inception in the late 1990s. NOAA is responsible for operating satellites, tide gauges, ocean buoys, and other observing systems to collect oceanographic data. Because many of these existing observing systems were designed to serve a particular purpose or collect specific types of ocean data, these data are not always available in formats that are easy to use or compatible with other data formats. IOOS represents a national effort to standardize and improve documentation of these data.

IOOS has two interdependent components: 1) a national coastal component and 2) a global component. The national coastal component of IOOS focuses on local to large scale marine ecosystems and consists of Coastal Ocean Observing Systems. These include oceanographic and meteorological observations, biological data, science products and services, and other information provided by a number of government agencies that monitor and manage the ocean environment along the coastal regions of the United States. The global component of IOOS is the U.S.A's contribution to GOOS. It emphasizes ocean-basin scale observations and consists of twelve complementary *in situ* space-based data and assimilation subsystems. These include tide gauge networks, moored and drifting buoy networks, environmental satellites, and ocean observatories. Ocean observatories are the systems that most commonly include (or have planned to include) hydrophones and other passive acoustic sensors. Examples of these are provided below.

The Ocean Observatories Initiative (OOI) is a Division of the Ocean Sciences program of the U.S. National Science Foundation (NSF). OOI funds the development of science, technology, education and outreach programs for an emerging network of science driven ocean observing systems. OOI is the National Science Foundation's contribution to the U.S. IOOS, which will feed data and research products into the Global Ocean Observing System. OOI took over the role of previous initiatives and programs (e.g. ORION & DEOS) and along with complementary NOAA efforts, now heads up the major Ocean Observatory projects in the United States.

Although there are several components of OOI, there is an emphasis on the development and deployment of three main types of observatories. These are based primarily on spatial scales of observation and data collection and consist of:

1) **Regional, Cabled Observatories** — Permanent and semi-permanent electrical and electro-optical cables connect multiple instruments to create an array of sensors over a relatively small area (10s to 100s of miles);
2) **Coastal Observatories** — A combination of cabled instruments, autonomous underwater vehicles, moorings, buoys, and floating platforms that are used to study the continental shelf (100s to 1000s miles); and,

3) **Global Observatories** — Buoys, moorings, autonomous devices, and radio and acoustic communications systems (such as acoustic modems and satellite telemetry) to collect data at ocean-basin and global scales (1000s miles +).

At present, the main focus of OOI is to develop several pilot and a few permanent observatories off of the east and west coasts of the United States that will serve as models for other long-term observatories worldwide. This initiative has taken various names and forms over the past few years. It is now taking shape in the form of several large research and development efforts, some of which are currently coming online in the Northwest Pacific. Many of these efforts are still in the planning, testing and initial implementation stages, and the details of their design and implementation are still evolving. A few examples of those that are operating or undergoing installation discussed below. A detailed list of those operating or planned to include hydrophones for passive monitoring is provided in Table 1A.

4.2.2 Eastern and Central North Pacific Observatories

There are several ocean observatories in existence off Hawaii and the west coasts of the U.S. and Canada (Figure 4). Some of the first ocean observatories developed in the Pacific were designed to conduct geophysical experiments and observations off Hawaii in deep-sea areas and re-used existing telecommunication cables that were no longer in use, but were still intact. The more recent and larger OOI efforts are being designed from the bottom up, and are focused on the Juan de Fuca Plate area off Washington and Vancouver Island in the Pacific Northwest (Figure 5).

4.2.2.1 HUGO -- The now defunct Hawaii Undersea Geo-Observatory (HUGO) was one of the first cabled deep-sea observatories in the United States. It was established by the University of Hawaii in 1997 at 1200 m depth on top of the Lohi Seamount, an active submarine volcano located about 50 nm due south of the Kilauea Volcano on the Island of Hawaii (Duennebier, 2002a). HUGO was connected to shore via a 47 km electrical-optical cable that provided power to the junction box at the terminal end where instrument packages were attached (Person et al., 2006). Although primarily a deep-water geological observatory, it included a hydrophone (sampling at a rate of 64 kHz). This system was able to record biological sounds, including humpback whale songs (Duennebier, 2002a). This was one of the first underwater scientific observatories not specifically dedicated to biological research that demonstrated the capability of recording marine mammals. Unfortunately, HUGO suffered a catastrophic failure from a short circuit of its cable in April 1998, but in its short lifespan demonstrated the capability for high-speed, high fidelity data-transmission from a remote, deep-sea site (Favali & Beranzoli, 2006).

4.2.2.2 H20 -- In September, 1998, the same year that HUGO failed, the Hawaii-2 Observatory (H2O) came on line. This observatory was located in 5000 m of water, approximately halfway between Hawaii and California (28 N; 142 W). H2O was a seafloor-seismic observatory that relied on a decommissioned co-axial AT&T telecommunications cable running between central California and Hawaii. The original cable was cut and terminated approximately 1750 km east-northeast of Honolulu, Hawaii and attached to a junction box (Butler et al., 2000; Chave et al., 2002). This recycled cable was used to provide two-way digital communications (up to 80 kbit/s via 8 digital ports) and 400W of power to the junction box (Petit et al., 2002). Instrumentation at the H2O site included a three-component seismometer and geophone, a pressure sensor, and a broadband hydrophone (Duennebier, 2002b). Data from the H2O system was streamed to the University of Hawaii from the cable terminus via the Internet. H2O was the first seafloor node to become part of the Global Seismographic Network. Humpback whale songs were among the sounds recorded from the H20 (Duennebier, 2002b; Stephen, 2003). However, there have not been any published studies of marine mammal bioacoustics using data from this observatory to date.

4.2.2.3 ACO -- The Station ALOHA cabled observatory (ACO) was established by the University of Hawaii in 2007. As with H20, an existing retired telecommunications cable was used as the main power and data connection cable to the observatory. This fiber-optic cable was actually retrieved from the seafloor, cut, and moved approximately 100 km to a location north of Oahu (22° 45'N, 158° 00'W) in a water depth of 4760 m. This location, known as "Station ALOHA" was an established sampling station used for oceanographic surveys. The observatory was installed in February, 2007 and ran nearly continuously until October 22, 2008 when it failed because of problems with the main connector for a replacement observatory that was being installed. Significant funding and resources are required for re-installation (a ship and ROV) will likely not be available. If a replacement observatory is funded, it will likely not be installed until 2010 or later. Any replacement observatory design includes a pair of hydrophones with a 196 kHz sample rate (Duennebier, 2009, pers. comm.).

The original ACO system collected hydrophone data sampled at 96 kHz. These data were sent to a shore station where they were low-pass filtered and sub-sampled to provide 2 channels of acoustic data, one at 32 kHz and the other at 160 Hz (for seismic monitoring). The acoustic data were archived at the University of Hawaii and also streamed in real-time to other users via the internet. Acoustic data collected from the ACO have been used to study seasonality in the relative occurrence of minke whale 'boings' and other marine mammal sounds (Oswald et al., 2008).

4.2.2.4 VENUS -- The Victoria Experimental Network Under the Sea (VENUS) is a fully operational cabled ocean observatory located on the inland waters off Vancouver Island (Dewey et al., 2009). It was designed as an undersea laboratory for ocean researchers and is maintained and operated by the University of Victoria, British Columbia. The first VENUS node was installed at 100 m depth in the Saanich Inlet in February 2006 (Dewey et al., 2007). About two years later in 2008, over 40 km of 'back-bone' cable and the last 2 nodes were installed in water depths of 300 m and 170 m in the Strait of Georgia, British Columbia (Round, 2008). These two separate geographic sites comprise the VENUS observatory (Figure 5). Although VENUS is a fully operational ocean observatory, it has been used primarily as a test-bed facility for various hardware (e.g. nodes), software, and infrastructure components of other larger observatory efforts such as NEPTUNE USA (now called "regional scale nodes") and NEPTUNE-Canada.

The VENUS ocean observatory was designed to address five primary requirements:

1) Remote access to seafloor observations;
2) High-speed and real-time connection to instruments;
3) Ability to control instrument sampling;
4) Unlimited power availability; and,
5) Easy and fast access to archived data.

The VENUS project utilized off-the-shelf networking equipment combined with traditional fiber-optic/electrical cables. This system provides power for instruments and transmits data and commands from scientists on shore and from the underwater instruments. The bandwidth of the fiber-optic transmission system from the nodes to the shore stations is nominally 100 MB/s (Ethernet), with expandable capability to 1 GB/s if necessary. The VENUS observatory utilizes 'trawl-resistant' (i.e. low profile, snag-resistant) nodes that function as junction-boxes by supplying power and data communications link to shore via the fiber-optic cable. The observatory is designed so that a variety of instrumentation and experiments can be temporarily or semi-permanently attached to each of the three nodes (Dewey et al., 2007).

Standard oceanographic instruments are connected through a Science Instrument Interface Module (SIIM), which can support multiple instruments through either serial or Ethernet protocols. Power from a SIIM is available at either 24 or 360 VDC, with added components providing intermediate voltages if required. Each SIIM can support up to 1.2 kilowatts of power (Dewey et al., 2009).

The high data bandwidth capability of the VENUS observatory provides the necessary infrastructure to record and monitor passive acoustic data from hydrophones. The hydrophone array system for VENUS was designed and built (by Svein Vagle and John Ford of Fisheries and Oceans, Canada) specifically for monitoring ambient noise and whales. The original system was too large to be easily deployed from the small vessels available, so a new design was made, consisting of fixed arms extending 4 m from a central structure (Macoun, 2007). This new system includes 3 hydrophones, each mounted on a removable tripod. Each tripod-hydrophone has 15 m of cable linking it to the central pressure case containing electronics. This allows the tripods to be moved and positioned to any desired location (up to 15 m), allowing a variety of spatial configurations of the hydrophone array.

This broadband hydrophone (7 Hz–100 kHz) system was designed to cover the frequency range of many cetacean vocalizations (i.e. killer whales) and other ambient noise (e.g. wind, lightening, rain, shipping noise). The data-acquisition system can be configured in a variety of ways, with individual hydrophones logging either raw audio or spectral data, at sample frequencies from 1– 180 kHz (Dewey et al., 2007). The maximum bandwidth (after an anti-aliasing) is 100 kHz (Barrodale Computing Services Ltd., 2004). A 16 bit digital acquisition with automatic variable gain can be used to optimize the dynamic range of these data. Raw data are stored in a single high compression data file. Data transmission rates can vary from 3 to 50 MB/minute. Automatic processing is used to extract data from each channel and produce both spectrogram plots and MP3 audio files that are stored in the data archival system for review and analysis later (Dewey et al., 2007).

4.2.2.5 NEPTUNE Canada / U.S.A (Regional Scale Nodes) -- The North East Pacific Time-series Undersea Networked Experiments (NEPTUNE) is one of the most ambitious ocean observatory projects currently being undertaken. A joint effort between the U.S. and Canada, its main goal is to establish a multi-disciplinary observatory network on the Juan de Fuca Plate, a marine geological feature located several hundred kilometers west of the U.S. / Canadian Border of Washington State and Vancouver Island, British Columbia. This effort is led by a consortium of academic and government research institutions.

NEPTUNE Canada is the Canadian component of the original NEPTUNE Canada/USA project. The goals of this component are shared with that of NEPTUNE/Regional Scale Nodes (RSN)-USA but are funded and managed by Canadian sponsors and institutions. The main cable installation, consisting of 800 km of cable, was completed in November 2007 (Best et al., 2008). The installation of five nodes occurred in July-August 2009 with the main instrumentation added later that year (Barnes, 2009). These nodes are planned to be networked with each other via an electrical/fiber-optic cable. The cable comes ashore on the southwest coast of Vancouver Island at Port Alberni and supplies the 10 kV DC power and high bandwidth data communications for the system. A 10 Gbit/sec Internet connection is being used to send data from the Port Alberni shore station to the University of Victoria for processing, dissemination, and for interactive control of the underwater system and its components (Best et al. 2008).

Once completed, the United States component of the original NEPTUNE project, Regional Scale Nodes (*formerly called NEPTUNE USA*) will be an expansive, multi-disciplinary ocean observatory network linking a variety of instrument packages and platforms (Howe & McGinnis, 2004). The 800 km of high-speed fiber-optic cable is planned to extend offshore to the Juan de Fuca Plate and terminate at two land-based shore stations, in Newport and Pacific City, Oregon. Attached to this cable will be numerous seafloor nodes (junction boxes). These nodes will supply hundreds of kilowatts of power at each node and up to 240 Gbit/sec data communications (RSN website; Chave et al., 2001). The observatory is in its initial stages of development. The five-year construction phase begin in September 2009, with nearly $106 million funding provided via the American Recovery and Reinvestment Act of 2009and $5.91

million in construction funds from the National Science Foundation (Consortium for Ocean Leadership, 2009). The observatory will consist of up to five instrumented nodes, and is projected to be completed by 2015. The goal is for data to flow from RSN's in situ sensors and instrument packages (attached to its nodes) to shore where it will be accessible to a variety of scientist, managers, educators, and other users (Delaney et al., 2000, 2001).

4.2.3 Northwest Atlantic Ocean Observatories

There are several operational ocean observatories off the east coast of the United States (Figure 6), however only one of these (SFOMC) includes permanent cabled hydrophones. The remaining observatories reviewed below have the infrastructure to easily attach hydrophones (e.g. via existing junction boxes), and the capability (e.g. available bandwidth) to transmit data to shore on existing data transmission cables, but as of this time, do not have acoustic data collection capabilities. There are several other ocean observatories and ocean observing systems (e.g. GoMOOS) in the northwestern Atlantic Ocean that either do not include hydrophones, or do not have infrastructure to easily attach hydrophones (e.g. via junction boxes) and, therefore, are not included in this review. Given the goals and vision of the OOI, it is likely that many existing and planned observatories in the northwest Atlantic will soon include permanent or semi-permanent hydrophones.

4.2.3.1 SFOMC -- The South Florida Ocean Measurement Center (SFOMC) is an Ocean Observatory located on the western boundary of the Straits of Florida (Figure 6). The shore facility is situated at the closest point to the Gulf Stream available along the US east coast at a location where the continental shelf break occurs only three miles from shore. The SFOMC provides a localized center for open ocean, coastal ocean, and estuarine science and ocean engineering research. It was founded through a partnership involving government and academia initially based on the U.S. Navy's Naval Undersea Warfare Center (NUWC) and Florida Atlantic Universities Ocean Engineering Dept. Several other universities and government agencies are now also part of this partnership.

The SFOMC shore-linked cables and high-speed multiplexers provide a multi-channel capability and a high-speed two-way communication link to the shore (Dhanak, 1999). A variety of environmental sensors are distributed across the measurement area, including fixed hydrophone arrays (Table 1A). Additional sensors include an ambient-noise sonar, deep and shallow water Acoustic Doppler Current Profilers (ADCPs), an autonomous underwater vehicle (AUV) docking station, and multi-sensor environmental arrays. An Ocean Surface Current Radar (OSCCR), a 5-head Acoustic Doppler Current Profiler (ADCP), a cyclosonde, and an ambient-noise sonar system are also installed on the range during process-study experiments (Dhanak, 1999).

Because of its many oceanographic research and monitoring assets, the SFOMC was selected by the U.S. Office of Naval Research (ONR) as an acoustic observatory that is utilized as a focal point for cooperative efforts between the passive sonar community and 'allied technologies' to provide a better understanding of the limits of passive sonar performance (Venezia et al., 2003). Although there have been no directed efforts to study bio-acoustics of marine mammals using SFOMC hydrophone arrays, one of the purposes of this acoustic observatory is to characterize the ambient acoustic environment. Undoubtedly, sounds produced by marine mammals are present in SFOMC ambient noise data-sets.

4.2.3.2 LEO-15 -- The Long Term Environmental Observatory-15m (LEO-15) is a regional coastal ocean observatory located in shallow water (10-16 m) off Tuckerton, New Jersey, that was established in 1996 (Schofield et al., 2002; Figure 6). It was one of the first ocean observatories in the OOI program. As with all OOI observatories, it provides two-way communication between the shore and instruments via junction boxes called 'nodes' (Table 1B). A 9 km-long electro-optic cable is connected from the shore to two nodes at 15 m depth (Forrester et al. 1997). The nodes provide multiple data and power ports for connecting a variety of instruments. A direct connection to the observatory is provided via the internet (Clark & Isern, 2003). To date, hydrophones for passive acoustic monitoring have not been deployed with LEO-15. However, the existing infrastructure is present to easily allow this capability.

4.3.3.3 MVCO -- The Martha's Vineyard Coastal Observatory (MVCO) is a shallow water coastal observatory located just 1.5 km offshore of South Beach, on the Island of Martha's Vineyard, MA (Edson, et al., 2000: Figure 6). The MVCA has three seafloor nodes located at 6 m, 12 m, and 18 m depths with a separation of about 1 km between each node (Table 1B). The nodes are connected via an electro-optic power and data transmission cable that is buried 1-1.5 m beneath the seafloor and is then fed into a 'sleeved-hole' across the beach and dunes to a shore-lab. A detailed description of the cable deployment process is provided in Edson et al. (2001) and McElroy et al. (2001). All of the nodes in the system are networked connections and are connected on a common Ethernet network located in the shore lab. The main focus of MVCO is to gain a better understating of the air-sea interface with the core instrumentation designed to investigate exchange of momentum, heat, and mass (McElroy et al., 2001). Acoustic instrumentation has been deployed for some research projects. However, these instruments and the project goals were focused on investigating physical oceanographic processes in the nearshore environment (Callaghan et al., 2008), not passive acoustic monitoring of marine mammals. Nevertheless, the necessary infrastructure to easily deploy hydrophones or hydrophone arrays is available with the MVCO and monitoring signals produced by marine mammals that might inhabit this near-shore environment is possible.

4.2.4 Test & Development Ocean Observatories

Test-bed observatories such as the Monterey Accelerated Research System (MARS, McNutt et al., 2003) (Figure 4), the Bermuda Testbed Mooring (BTM, Figure 6), and the HALE-ALOHA Moorings Program, are being used to develop and test new systems and instrumentation for eventual use in other more permanent ocean observatories. These ocean observatory facilities are usually located close to shore in deep water (e.g. MARS & BTM), providing ready access to instruments, junction boxes and shore facilities. Although these systems have the capability and infrastructure to easily attach hydrophones and transmit broadband data to shore, they do not typically include permanent or semi-permanent hydrophones as part of their default configuration (Table 1B).

4.2.5 European Ocean Observatory Initiatives

The European counterparts to the OOI and IOOS - the European Sea Floor Observatory Network (ESONET) and its partner organization the European Multidisciplinary Seas Observation (EMSO) - are currently in the planning and initial development stages of their ocean observatory programs. ESONET is the underwater component of the European Global Monitoring for Environment and Security (GMES) and is intended to provide strategic, long-term monitoring capability in geophysics, chemistry, biochemistry, oceanography, biology, and fisheries science for its European members. This effort is similar in its technical goals and vision to the cabled observatory component of OOI, but proposes to develop as many as ten seafloor observatory networks at coastal and deep-water sites across Europe. The EMSO effort is based on collaborations between the academic community and industry with a goal to further the development of technology within the ESONET initiative.

Implementation of EMSO initially will be based on extending existing systems by connecting previously autonomous systems to cabled power to provide long-term, real-time data collection capability. Also planned is the integration of re-locatable and mobile 'seafloor lander' platforms, primarily intended for marine geological research. A phased development is proposed, initially based on deployment of conventional autonomous or satellite telemetry observatories at a few key sites, and eventually leading to the development and integration of a fully cabled ocean observatory system. Once completed, the entire system is expected to be comprised of approximately 5000 km of underwater fiber-optic cables linking observatories to the land via nodes on the sea floor. The cables will provide power to observatory instruments and two-way real-time data telemetry using internet protocols (IP). Researchers will be able to deploy instrumentation and sensor packages, including hydrophones, at ESONET sites by linking to junction boxes at each location.

The ESONET federation will oversee standards and data management and will coordinate observatory deployment. Similar to the IOOS, data will be interfaced with, and distributed to, national and international data centers. A few important examples of those already developed or in the process of being implemented provided below.

Because most of the ESONET observatories are in the planning or development stages, it remains to be seen if they will all be developed as planned, especially given the current difficult economic climate. Most of the existing observatories are small coastal efforts with an emphasis on marine geological science. However, a few technologically advanced observatories such as deep-sea 'neutrino' detection telescopes are already operational. These systems include significant infrastructure, complex designs, and sophisticated technologies to collect their data from numerous calibrated sensors that include hydrophones and hydrophone arrays. A few examples of these, especially those from which marine mammal data have been collected are reviewed here.

4.2.6 Neutrino Observatories

As part of ESONET's initial effort, deep-sea observatories have been designed and developed to function as underwater 'neutrino detection telescopes'. These systems incorporate optical and acoustical sensors that are used to detect 'ultra high energy' sub-atomic neutrino particles at deep ocean depths (Niess & Bertin, 2006). The deep ocean is an effective barrier that shields these sensitive sensors from the cosmic radiation that is constantly bombarding terrestrial sites and results in problematic background noise. The two main operating systems are the Neutrino Mediterranean Observatory (NEMO) and the Astronomy with a Neutrino Telescope and Abyss environmental REsearch System (ANTARES) observatories, both located in the Mediterranean Sea (Figure 7). Both of these systems include extensive deep-water hydrophone arrays (Table 3). The NEMO system was the first operating real time node for ESONET (Favali et al., 2007) and has been used to study several species of marine mammals, including sperm whales and dolphins (Pavan et al., 2008; Riccobene et al., 2009).

4.2.6.1 NEMO -- The NEMO is located in a water depth of approximately 2000 m, 25 km east (offshore) of the port of Catania, Sicily. It consists of a 28 m long electrical/fiber-optic cable connected to a shore laboratory to provide power and real-time data-transmission. This observatory has been operating since 2005, and has gone through various modifications and upgrades. A project named PEGASO, is aimed at developing better infrastructure and management of deep-sea scientific studies using NEMO's facilities and collaborations (Favali et al., 2007; Favali, & Beranzoli 2007). In 2005 and 2006 a team of scientists from the University of Pavia (CIBRA) and the National Laboratory of the South, Catania, Italy (INFN) collected acoustic data from NEMO as part of the Ocean Noise Detection Experiment (ONDE; Pavan, 2008; Riccobene et al., 2006). The goal of ONDE was to conduct a real-time experiment to monitor acoustic signals in deep waters of the Mediterranean Sea (Riccobene et al. 2009) The primary focus was to characterize natural ambient noise, man-made noise, and biological sounds recorded from NEMO between January 2005 and November 2006. At 20 km from shore, the cable was divided into two branches, approximately 5 km each, to reach two separate study sites, a north site (37° 30' 810 N, 15° 06'809 E) and a south study site (37°30'008 N, longitude 015°_23'034 E), Removable titanium 'frames' containing experimental apparatus were deployed at each site on the seafloor. The north site frame was connected to a seismic and environmental monitoring station called the Submarine Network 1 (SN-1), which is the only cabled node of the ESONET. The cable leading to the south site was connected to the ONDE station for monitoring deep water ambient noise (Riccobene et al., 2009).

Data from the ONDE station were sampled using four broad-band hydrophones (30 Hz - 50 kHz) digitized underwater, and transmitted to the shore station via the fiber-optic cable (Riccobene et al., 2009). The hydrophones were continuously sampled at a rate of 96 kHz (24 bit resolution), and later using a 5 minute/hr duty cycle (Pavan et al., 2005). More than 2 TB of acoustic data were stored to hard drives for post-processing. Data processing was performed using a custom software tool called SeaRecorder (Riccobene et al., 2009). Among the various types of biological sounds detected were clicks from sperm whales and striped dolphins. Time-differences of arrivals (TDOA) were calculated to determine animal tracks in 3-D space for select recordings of these species (Pavan et al., 2008).

4.2.6.2 ANTARES/AMADEUS -- The ANTARES telescope is a neutrino detector which has two main purposes: high-energy astronomy and the search for dark matter (CNRS, 2006). A related project called Antares Modules for Acoustic Detection Under the Sea (AMADEUS) was recently integrated into the ANTARES neutrino telescope (Lahmann, 2008). ANTARES is located 40 km south of Toulon, France, at a depth of 2500 m in the Mediterranean Sea. AMADEAUS consists of a series of vertically configured 'acoustic storey' instrument packages. Each storey includes six broadband hydrophones in 2 sets of 3 equilateral triangles with approximately one meter spacing between each (Figure 8 A/B). The acoustic storeys are located along a vertical line at various depths (180-410 m) above the seafloor (e.g. all less than 2000 m), with a maximum distance of 340 m between adjacent storeys.

Two types of sensors are contained in the storeys: 1) hydrophones and 2) 'acoustic modules.' The acoustic modules are attached to the inside of spheres which are used as part of the 'optical module' with the idea of combining the two types of sensor modules in the ANTARES neutrino telescope design. The hydrophones are mounted facing upward, thus providing good horizontal and upward looking receiving sensitivity. The acoustic sensors are flat (+/- 3 dB) from 1 to 50 kHz (sensitivity of -145 dB re: 1V/uPa including the preamplifier), however the system is capable of recording acoustic signals up to 100 kHz. Although the ANTARES/AMADEUS system has been used to study natural ambient noise (e.g. sea-surface waves), no dedicated studies of marine mammal sounds have yet been conducted. This system would be ideal for recording clicks of deep-diving animals such as beaked whales, pilot whales and sperm whales, similar to studies being conducted using the NEMO.

4.2.7 Polar Observatories

Polar region ice caps provide an ideal natural setting for deploying semi-permanent and permanent ocean and acoustic observatories. Ice can provide a stable platform that can be drilled through to provide easy access to the ocean below. Hydrophones can be deployed through holes in the ice and easily retrieved for maintenance. In 2005, a permanent 'perennial' acoustic observatory was established in the Antarctic by the Alfred Wegener Institute (AWI) for Polar and Marine Research, Bremerhaven, Germany.

The Perennial Acoustic Observatory in the Antarctic Ocean (PALAOA) was established in December of 2005 on the Ekstrom Ice shelf in the Weddel Sea, about 15 km north of the German Neumayer Base (Klinck, 2008; Boebel et al., 2006; 2008). This system consists of 2 hydrophones that were deployed through boreholes in the ice-shelf (Table 2). The hydrophones are hung 70 m below the bottom of the ice shelf, and about 90 m from the bottom of the seafloor (Klinck, 2008; Boebel et al., 2006).

The PALAOA station is autonomously operated and remotely controlled. The station is powered by solar panels and a wind generator, and uses a methanol fuel cells and batteries for emergency and backup power. Data from the hydrophones are recorded at up to 192 kHz at 24 bit resolution, resulting in up to 140 GB of data per day. These high-quality (uncompressed) data are stored locally on a hard drive and shipped twice a year from Neumayer Base to Germany. In parallel, a compressed data stream (sampled at 48 kHz/16bit) is sent from PALAOA via a wireless LAN radio link to the German Neumayer Base. Here, the data are again compressed and sent via satellite to the AWI in Germany for real-time data analysis and archiving.

Numerous calls from marine mammals have been detected in this dataset, including seals (mostly Weddell seals), killer whales, blue whales, fin whales, and minke whales. Man-made and natural sources of noise are being recorded and analyzed, including extremely loud (> 200 dB re 1 uPa @ 1m) natural events due to iceberg collisions (Boebel et al., 2006; Kindermann et al., 2008). One of the goals of collecting these recordings is to determine a long-term noise budget in a relatively pristine location as well as to identify and quantify acoustic sources in the Weddell Sea (Klinck, 2008; Kindermann et al., 2008).

5 Discussion

Cabled hydrophones provide long-term passive acoustic monitoring capabilities that are not constrained by weather, equipment maintenance, data storage, power and other issues that affect other fixed PAM technologies (e.g. autonomous recorders and radio-linked hydrophone systems). However the cost of building and deploying large-scale cabled systems can be prohibitive. Thus, such projects are usually restricted in scope, or else must be funded by large government and inter-governmental agencies with large budgets. Also, it is not usually easy to relocate the hydrophones once they have been deployed, so site selection is critical.

Two important aspects of hydrophone arrays that should be considered when designing a system are the number and spatial configuration of hydrophones. These two aspects will dictate how the system will perform when detecting, locating and tracking marine mammals from calls. Systems that use only single hydrophones are typically not able to localize signals (except when sophisticated signal processing can be performed). Hydrophone arrays, however, provide the ability to determine bearings to sound sources and, depending on their configuration, can localize the source of sounds, using time-of-arrival differences beamforming, or other signal processing methods.

Radio-linked hydrophones can provide more flexibility than cabled hydrophones because they moved to other sites, or removed for maintenance or replacement. However, radio-linked hydrophones require a greater level of maintenance (and therefore additional costs) for continued operation. In addition, there are often user/subscriber or data-transmission costs associated with satellite and cellular communications that can become significant if transmissions are frequent or high-bandwidth data are being sent. The development of 'intelligent' systems that incorporate signal detection, processing and even classification, has allowed lower bandwidth and less frequent communications to shore. However, the downside to this approach is that these systems must 'target' specific types of signals or measurements, which means some information is lost in the processed data stream that is transmitted to shore. Some systems (e.g. PALAOA & CTBTO's Hydroacoustic stations) use a combination of local data-archiving or buffering and data telemetry to provide remote monitoring capability while also allowing a full record of the data to be kept.

Ocean observatories have great potential for fixed PAM monitoring of marine mammals. Because of their permanent nature and, in many cases, extended spatial coverage, long-term monitoring of large areas using ocean observatory sensor networks is possible. In addition, their design and infrastructure (e.g. junction boxes) allows multiple sensors to be deployed in a wide range of configurations. This flexibility, combined with a degree of permanence (i.e. long term monitoring) provides capabilities that few other fixed PAM systems can offer. VENUS is a good example of a permanent hydrophone system that was designed to collect information on marine mammals (primarily killer whales) but that allows flexibility in the spatial configuration of the hydrophone arrays. Such flexibility is essential for collecting data on a variety of marine mammal species, or to answer questions about the acoustic behavior and ecology.

Most of the existing and planned ocean observatories are not located in areas of oil and gas production or exploration activity. Therefore, their relevance for the Oil & Gas Industry's needs is limited with respect to geographic considerations. However, the OOI and ESONET programs are developing many of the technologies and methods required for implementing and maintaining cabled, and in some cases, radio-linked hydrophone systems. There are a host of research and engineering scientific organizations that are providing or developing the expertise needed to develop and operate ocean observatories. A new industry is developing around this new area of research and technology. Soon, many of the important components of this system (e.g. power nodes and acoustic monitoring systems) may become commercially available. More importantly, these technologies will be field tested and in many cases their effectiveness for monitoring marine mammals will be demonstrated. Most of the observatories presented here are in their initial stages of development and implementation so there will undoubtedly be many lessons learned that can be applied to future fixed PAM systems. The development and implementation of any new system will require careful planning, consideration and in most cases, customization with respect to the specific needs and goals of the end users.

Important considerations in the configuration and design aspects of any fixed hydrophone system for monitoring marine mammals include (but are not limited to) the species of interest, the area to be monitored, the ambient noise characteristics and acoustic propagation characteristics in the study area, and perhaps most importantly, the biological questions that are to be addressed. These basic considerations must be clearly understood to design and configure a fixed passive monitoring system intended for use on marine mammals.

The large volumes of data (e.g. up to terabytes of data per day or week) collected by these systems will require more sophisticated and reliable data processing methods. For example, automated detection and classification will be required (see chapter by Oswald et al., this volume) to identify, extract and categorize sounds recorded or monitored from fixed hydrophone systems. Additional acoustic data processing and analysis needs to include automated or semi-automated algorithms for sound source localization, tracking and eventually, abundance estimation of calling animals. These data-processing and analysis techniques will need to be developed in tandem with fixed-PAM technology development and implementation or there will soon be a backlog of data that will need to be analyzed. Finally, the results of these processed acoustic data must be placed within a biological framework in order to understand their significance to the animal populations of concern to the oil and gas production and exploration industry. Progress is being made on all of these fronts; however, additional advancements will be necessary if important issues relating to marine mammal biology, conservation and management are to be addressed.

5.1 A Way Forward

Oil production and drilling platforms and islands can provide much of the necessary (and most costly) components of the infrastructure needed to install and implement cabled and radio-linked hydrophone systems. These platforms and islands can provide power, communications links, and a physical structure in the ocean to secure cables and equipment. This will allow significant savings in installment costs, due to reduce cable lengths one of the most expensive component of cabled hydrophone systems. Cables and instruments could be attached to oil drilling and production platforms before they are deployed so that only a relatively short cable would be required to get the hydrophones away from the platform. Such an approach could further reduce the costs of installation and deployment. Data collection and archive could occur on these platforms and archived data (e.g. hard drives) could be physically transported to a shore-based facility for post-processing, using existing transport vessels and aircraft. It is also feasible that real-time monitoring and signal processing could be conducted on platforms or remotely from shore (e.g. via the internet). Processed data could be physically transported to shore. Using existing oil and gas industry infrastructure makes cabled-hydrophone systems more affordable and therefore viable. These savings and benefits should be considered carefully when comparing cabled and radio-linked hydrophone systems to 'traditional' monitoring methods.

Radio-linked hydrophone systems can also be improved by utilizing existing infrastructure. Existing internet connections on platforms could be used to remotely control a computer located on the platform. This would eliminate the requirement of having a human operator on the platform to monitor or process acoustic data. For example, oil production and exploration platforms can provide high-relief for mounting antennas for transmitting raw or processed data from cabled hydrophones by radio-waves, cell-phone carriers, or satellite links to shore. The increased heights above the ocean surface should greatly improve transmission distances, especially where line-of sight transmission paths are required (e.g. VHF and cell-phones). Relay stations could also be designed when line of sight or other distance-limited radio-transmission methods are used. The South Atlantic Bight Synoptic Offshore Observational Network (SABSOON) system of the southeast coast of the United States provides a good example of a system that was developed based on existing platforms and infrastructure and could be used as a model for using oil and gas production platforms.

The occurrence of multiple platforms in an oil production or exploration area would allow arrays of hydrophones, or a network of hydrophone systems to be developed cost-effectively. This would greatly increase the capabilities of the hydrophone system to allow much greater geographic coverage and also provide the possibility of tracking individuals and groups of animals (i.e. by spatially configuring hydrophones closely enough to pick up the sounds from individuals on multiple hydrophones). There are numerous possibilities for designing cabled and radio-linked systems that can benefit from the infrastructure available with existing oil drilling and production platforms. The engineering and technical details of designing a system based on existing platform infrastructure are beyond the scope of this review, but should be considered carefully when choosing an appropriate system.

In some cases technologies will need to be developed and customized according the needs of the user. For example, the radio-linked right whale detection buoy system developed by Cornell University and the Woods Hole Oceanographic Institute is an example of fixed PAM technologies developed to address a specific problem for a single species. This system is capable of acoustically identifying and monitoring the presence of a single species of whale. This information is used to notify large vessels in order to mitigate the effects of shipping activities in the Boston Harbor area.

'Off-the-shelf' technologies and 'turnkey' technologies are becoming available for fixed PAM and merit some consideration, especially in cases where development and designs of new systems are limited by time and user expertise. For example the Rapidly Deployable Systems Technology (RDST) developed by Defense R&D Canada is an off-the-shelf system that is designed to provide a flexible configuration and can be deployed and operated from existing platforms. Another example is Seiche Measurments Ltd.'s, radio-linked hydrophone (Seiche Buoyed System) that was originally developed to conduct real-time monitoring of well heads undergoing decommissioning (Pierpoint & Gill, 2005).

One advantage of turnkey systems is their greater ease of operation. However their disadvantage is that they can be limited in their configuration and capabilities. A suitable compromise can be reached with a system with some degree or user-specification and customization, to provide the type of information needed to the end-user, but with sufficient ease of operation to allow non-experts to deploy and operate them.

When designing or choosing fixed PAM systems for monitoring marine mammals, it is important to consider the biology and behavior of the species of interest. Questions and issues to be addressed must be clearly defined so that appropriate combination of methods and technologies can be used to collect relevant data. For example, a system that is designed to study the acoustic behaviors and movements of large baleen whales (e.g. blue and fin whales) would have very different capabilities (e.g. good low-frequency response, low sample rate / bandwidth and data-transmission capabilities) than one intended to study the occurrence of coastal delphinids or deep-diving beaked whales (e.g. good high frequency response, high sample rate / bandwidth, and data /transmission capabilities).

Important considerations in fixed PAM design and capabilities should include the frequency band of sounds produced by the species of interest, the source levels their sounds (if available), and the scale over which monitoring is desired. A system intended to detect the occurrence of animals near platforms could consist of single hydrophones deployed near each platform, but operated independently, whereas a system intended to localize and track animals would likely consist of a hydrophone array with a sufficient number or hydrophones and appropriate spacing to allow localization and tracking over ranges of interest. In the latter case, this would probably require a system with many hydrophones recorded (or transmitted) via a time-synched system or better, a multi-channel data recording/transmitting system. Due to the large amounts of data can be generated from such system, automated or semi-automated, detection, localization and other signal processing software need to be considered (See Oswald et al, this volume)

Other important considerations for the design and selection of fixed PAM systems include noise characteristics (including natural, man-made and monitoring system noise). This may require characterizing the ambient noise, especially noise related to the platforms and their associated machinery in the monitoring area. Oceanographic characteristics, and propagation conditions can greatly affect detection rates and ranges of localization. This may require characterization of thermoclines, surface ducts, downward or upward refracting ocean environments, surface roughness, and substrate type. Baseline monitoring may be required before oil and gas exploration and production activities occur, so that comparisons of acoustic data collected from marine mammals before, during and after oil and can be made.

5.2 Summary

There are many examples of fixed cabled and radio linked systems that have been used to effectively study and monitor marine mammals. Existing and planned ocean observatory and new dedicated marine mammal acoustic monitoring systems are improving the technologies and capabilities needed for monitoring and mitigation of oil and gas exploration and production activities on marine mammals. To effectively utilize existing systems and design new ones will require an understanding of the biology and acoustic behaviors of the species targeted for monitoring, information about ambient noise and propagation characteristics of their habitats, as well as a clear definition of the scientific and/or management goals of the monitoring efforts.

The examples provided here should serve as a starting point and basis for the design and implementation of other systems. The specific needs of the users must be carefully considered when selecting which technologies are appropriate to use. Finally, a clear idea of how the data collected from these systems will be processed and analyzed is needed before undertaking any efforts in monitoring with these high data-generating technologies. The challenges that lie ahead in the development, installation, maintenance and use of fixed PAM technologies are considerable, but not insurmountable. Great progress has already been made, and numerous systems are currently being used to effectively monitor marine mammals and mitigate human activities. The future of fixed PAM methods for remotely monitoring marine mammals and mitigating human activities is promising and should lead to many new discoveries and effective solutions.

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6 Tables

Table 1A. U.S. and Canadian cabled ocean observatories with permanent hydrophones installed or planned for 2010.

Name	Location	Depth (m)	# of nodes or junction boxes	# of hydro-phones	Spatial hydrophones configuration	Hydrophone bandwidth	Sample Rate	Comments
ALOHA Cabled Observatory[3] (ACO)	22.75° , -158.00° 100 km NW of Oahu	4760	1 junction box	1	N/A	96 kHz	Two channels @ 32 kHz & 162 Hz	ACO is currently not operational [4]
NEPTUNE - Canada[5]	49° , -126° Juan de Fuca plate (off West Vancouver Island, B.C.)	17 - 2,660	6 nodes and multiple junction boxes[6]	5-6	3 (more planned)	5 Hz-300 kHz		The largest cabled seafloor observatory in the world consisting of an 800 km cable loop. Live data-feeds to website[7]
Regional Scale Nodes [7] (NEPTUNE-USA)	45°, -125° Juan de Fuca Plate (off Washington and Oregon coasts)	Up to 300m depths planned	7 nodes scheduled (more planned)	TBD	TBD	TBD	TBD	RSN is still under construction. Cable installation is planned for 2010.
VENUS[8]	48.40°, -122.55° Saanich Inlet & Strait of Georgia, Canada.	100-300	3 nodes	3	Mounted on three removable tripods 3 meters in length at 120 degree radial intervals [9]	4 -100 kHz[10]		VENUS was developed as a 'testbed' observatory. Hydrophone array deployed at Strait of Georgia East Node
SFOMC[11]	26°, -80° 3 miles off shore of Ft. Lauderdale, Florida	20, 50, 256	> 500	Multiple	Cabled hydrophone arrays	Narrow and broadband	unknown	Details on the acoustic sensors are limited. See SFONMC information page for details[12].

[3] http://www.soest.hawaii.edu/GG/DeepoceanOBS/aco_home_page.htm
[4] The Aloha cabled observatory experienced a failure on 22 Oct 2008. A repair date has not yet been scheduled. Dr. F. Duennebier, pers. comm.
[5] http://neptunecanada.ca
[6] http://www.ooi.washington.edu (NEPTUNE-USA was renamed Regional Scales Node in 2009).
[7] https://dmas.uvic.ca/Login
[8] http://venus.uvic.ca/
[9] Macoun, 2007; http://venus.uvic.ca/facility/instruments/hydrophone.php
[10] Dewey et al., 2007
[11] http://www.sfomc.org/

Table 1B. Ocean observatories with non-permanent hydrophones or hydrophone ready nodes/junction boxes.

Name	Location	Depth (m)	# of nodes or junction boxed	# of hydro-phones	Spatial hydrophones configuration	Hydrophone bandwidth	Sample Rate	Comments
MARS[13]	36.35° , 121.6° Monterey Bay, California	891	1 node	1 (seis-mometer)[14]	N/A	< 50 Hz	Up to 1000 Hz	MARS was developed as a 'test-bed' observatory and is capable of hydrophone connectivity.
LEO-15[15]	39.4°, -74.1° Off Tuckerton, NJ	10-16	2 junction boxes	none currently	N/A	N/A	N/A	Junction boxes can support hydrophones
MVCO[16]	41.3366°, -70.5564° 1.5 mi offshore, Martha's Vineyard, MA	6, 12, 18	3 nodes	none currently	N/A	N/A	N/A	Acoustic instrumentation has been deployed for some research projects
BTM[17]	32.4°, 64.7° 80 km SE of Bermuda	4500m	N/A (radio-linked system)	none currently	N/A	N/A	N/A	Infrastructure should support hydrophone connectivity. 'Inductive-link' telemetry system used to transmit location and meteorological data to shore.

[12] http://www.sfomc.org/SFOMC%20OCEAN%20OBSERVING%20SYSTEM%20102903.pdf
[13] http://www.mbari.org/mars/
[14] Guralp CMG-1T (manufacturer / model) three-component seismometer
[15] http://marine.rutgers.edu/mrs/coolresults/2005/glenn_SSC_2006.pdf
[16] http://www.whoi.edu/mvco/description/description2.html
[17] http://www.opl.ucsb.edu/btm.html

Table 2. Radio-linked hydrophone passive acoustic monitoring systems

Name	Location	Depth (m)	Method of radio-telemetry	# of hydro-phones	Spatial hydrophones configuration	Hydrophone band(width)	Sample Rate	Comments
Cornell / WHOI Right Whale Detection Buoy System	Shipping Lanes off Boston Harbor	Shallow (20 - 40m) coastal waters	Cellular and satellite phone network	10	Linear, L –shaped array.			Near real time updates of right whale detections via a dedicated website[18]
DFO-Canada / ISMER PAM Buoy system[19]	Saguenay-St. Lawrence Marine Park	40-120m	900 MHz and Iridium satellite link	2-5	Large aperture (20 – 40 km) sparse array	< 2 kHz		Various spatial configurations tested[20]
PALAOA[21]	Near Neuymayer Station, Antarctica	70m mid-column (in 160 in H_20 depth)	Wireless LAN to local base station / satellite link to main lab in Germany	1[22]	N/A	96 kHz	192 kHz	Raw acoustic data stored locally. Compressed data transmitted to base and then to main lab in Germany[23]
CTBTO / IMS Hydroacoustic Stations[24]	Worldwide (see Figure 2)	Hydro-phones located in SOFAR channel	2 way satellite link to Vienna headquarters.	1	2 arrays on opposing sides of oceanic islands for new stations.	(< 100 Hz)	240 Hz	6 Hydroacoustic stations [25] mostly located off oceanic islands. Data buffered locally, then transmitted to HQ
Seiche Buoyed (PAM) System	Semi-permanent / relocatable	12-16 m	UHF (1 G Hz)	Up to 6	2 vertical array	2 – 200 kHz		Relatively short transmission range. Power on/off can be controlled remotely.
QUEphone	Drifting	Up to 2000m (dives)	Satellite uploads of up to 1000 data-'event' files	1	N/A	44 kHz[26]	100 hz[23]	This is considered a hybrid system. Incorporates AR and RLH technologies.

18 http://www.listenforwhales.org/NetCommunity/Page.aspx?pid=430
19 http://www.qc.dfo-mpo.gc.ca/Biblio/Gen/AuthorsIML_ROY_215.asp
20 Simard et al. 2008b.
21 http://www.awi.de/en/research/new_technologies/marine_observing_systems/ocean_acoustics/palaoa/
22 Two hydrophones were originally installed but only remained operational. Klinck, pers.comm.
23 http://epic.awi.de/Publications/Kin2008b.pdf
24 Lawrence & Grenard, 1998
25 http://www.seismo.ethz.ch/bsv/ctbto/ims/hydro.html; map of acoustic station: http://www.ctbto.org/map/
26 Matsumoto et al. 2006. Sample rates may have been increased since this publication. Contact lead author haru.matsumoto@noaa.gov for latest information:

Table 3. Neutrino observatories with hydrophones that have or can be used to monitor marine mammals.

Name	Location	Depth (m)	# of nodes or junction boxed	# of hydro-phones	Spatial hydrophones configuration	Hydrophone bandwidth	Sample Rate	Comments
NEMO-ONDE	21 km off the port of Catania, Sicily	2050 Ht	1	4	Hydrophones mounted in a tetrahedral configuration 1m per side [27]	30-50 kHz[28]	100 kHz	Work on marine mammals conducted by CIBRA as part of the ONDE project[28]
ANTARES/ AMADEUS[29]	40 km south of Toulon, France	2050	1 junction box (feeds into 6 acoustic storeys)	1800	Each storeys includes 6 hydrophones configured in 2 sets 3 in an equilateral triangle with 1m spacing.[30]	100 kHz	250 kHz	For technical details see Lahmann et al. 2009.

[27] Riccobene et al. 2009.
[28] http://www-3.unipv.it/cibra/res_nemo_uk.html
[29] http://antares.in2p3.fr/index.html
[30] http://antares.in2p3.fr/Overview/detector.html

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7 Figures

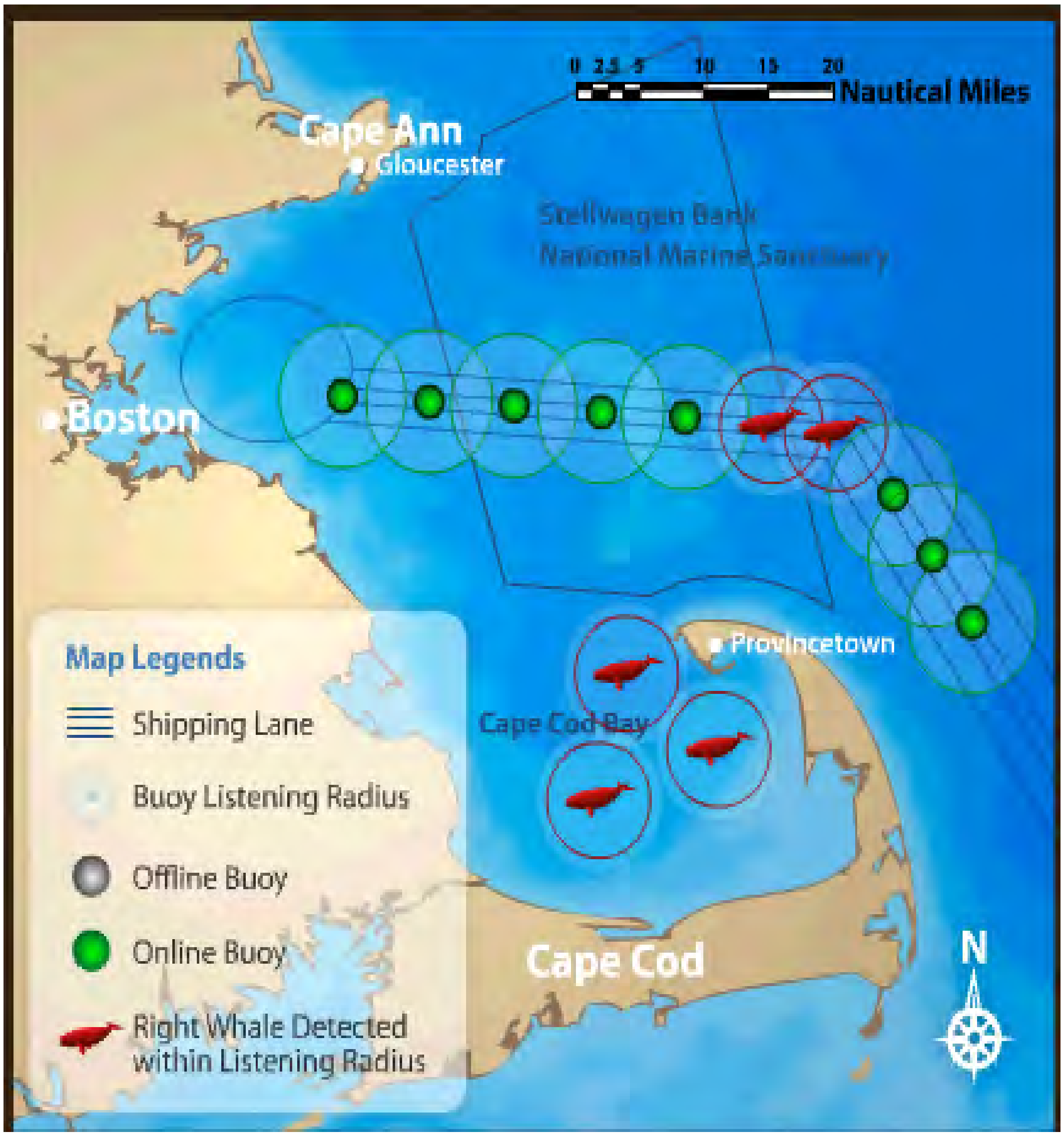

Figure 1. Example of the live display of right whale detections from Cornell/WHOI auto-detection buoy system in the Stellwagen Bank region off Boston Harbor. (http://www.listenforwhales.org/).

Figure 2. Comprehensive Test Ban Treaty Organization's International Monitoring System of hydroacoustic station locations. (from http://www.seismo.ethz.ch/bsv/ctbto/ims/hydro/html)

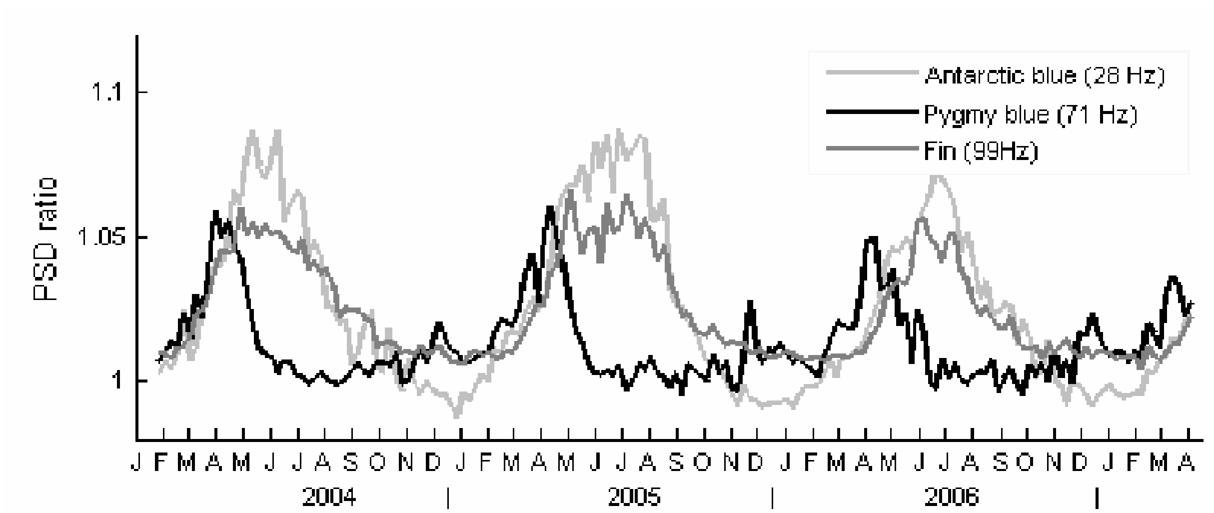

Figure 3. Processed acoustic data from the CTBTO/IMS hydroacoustic station at Cape Leeuwin, Western Australia**.** Graphs indicate Power Spectral Density ratios of different frequency bands representing call types from what are considered to be different blue and fin whale populations by the authors.
(reprinted with permission from Gedamke et al., 2007).

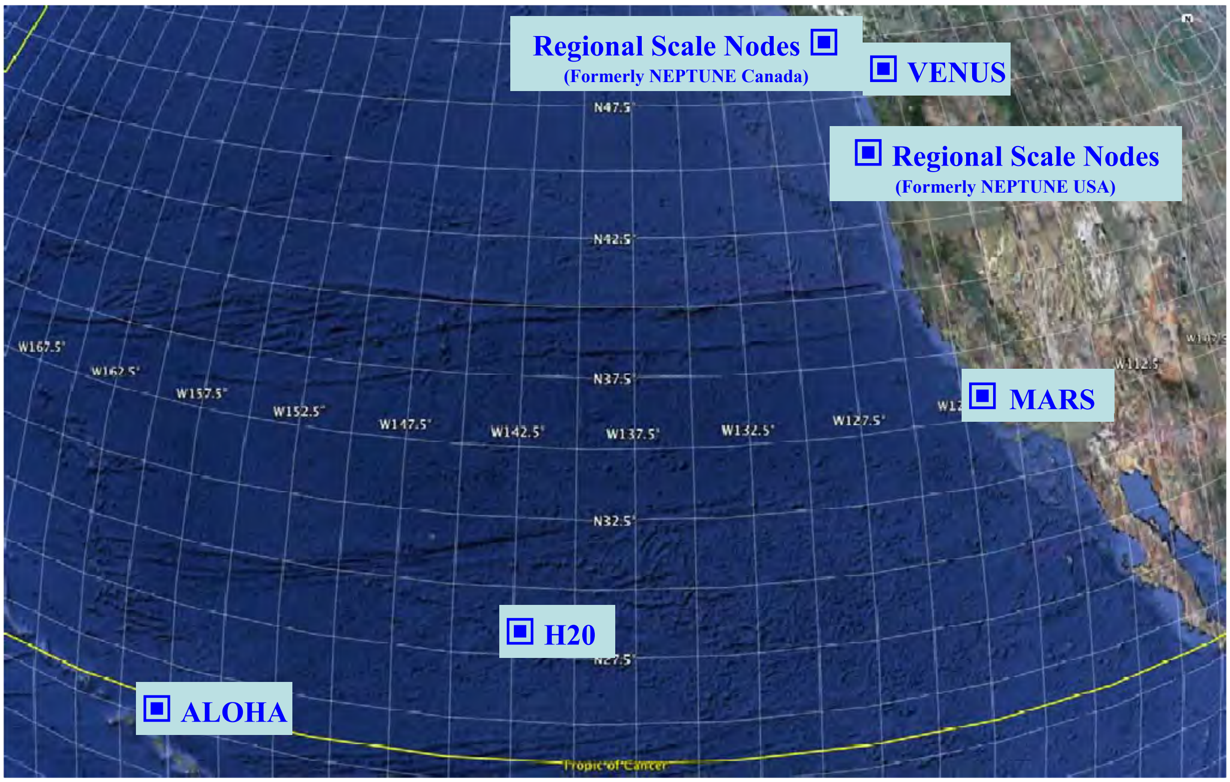

Figure 4. Map of ocean observatories that have planned or have demonstrated passive acoustic monitoring capabilities in the central and eastern North Pacific Ocean

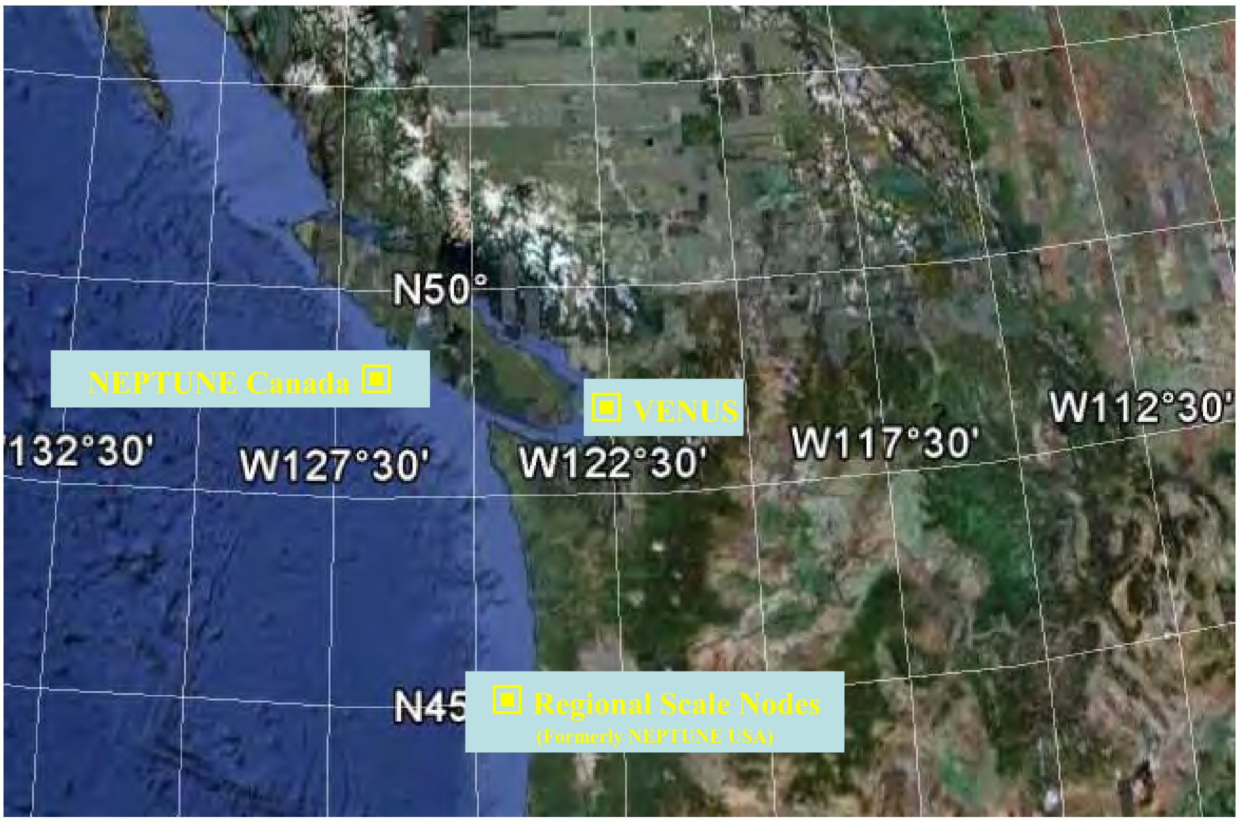

Figure 5. Map of ocean observatories that have planned or have demonstrated passive acoustic monitoring capabilities in the Northwest Pacific region of the USA and Canada.

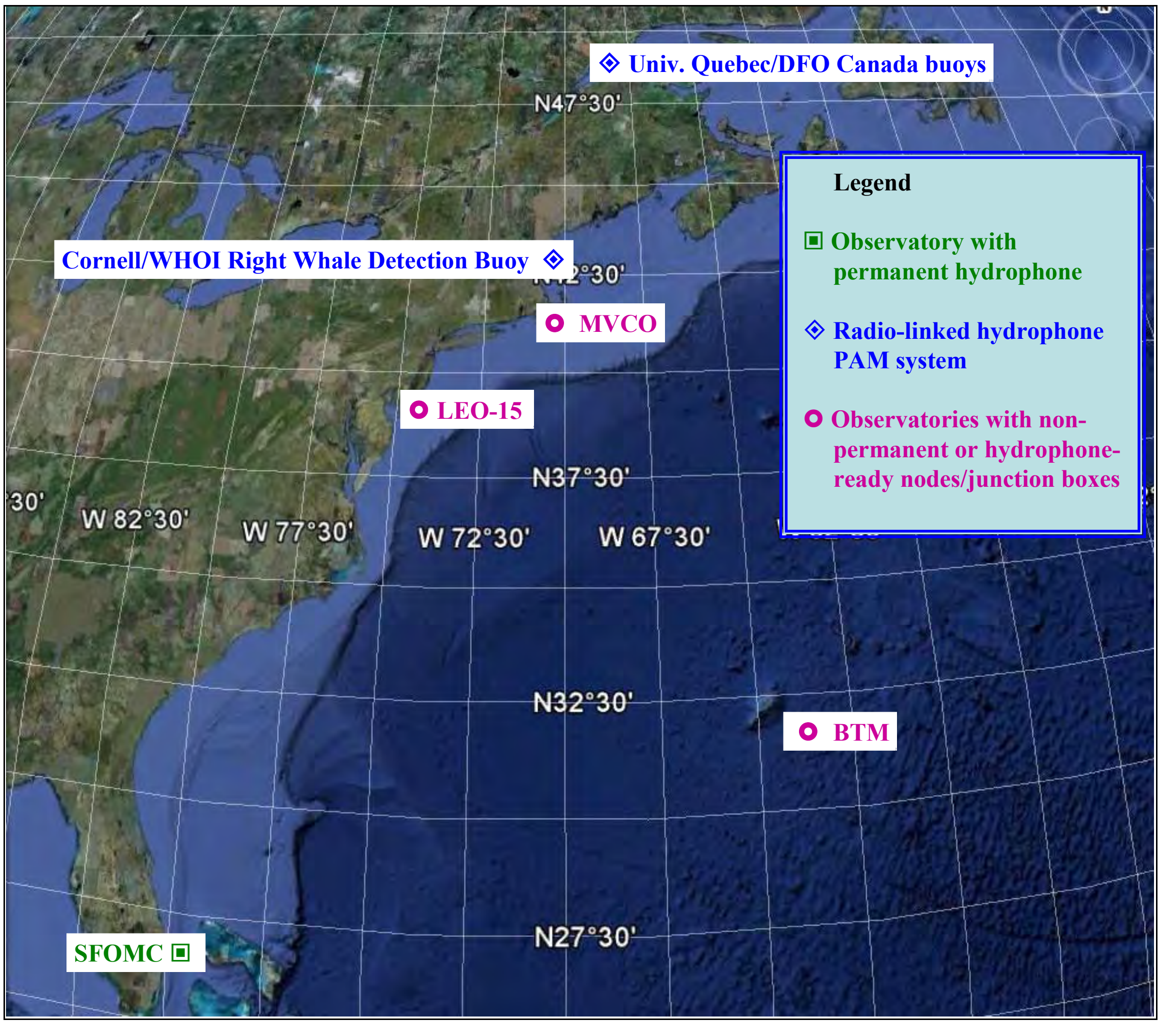

Figure 6. Map of ocean observatories that have planned or have demonstrated passive acoustic monitoring capabilities in the Northwest Atlantic Ocean.

Figure 7. ESONET (EU) neutrino observatories in the Mediterranean Sea. These neutrino observatories include hydrophones that have, or can be used to monitor marine mammals sounds.

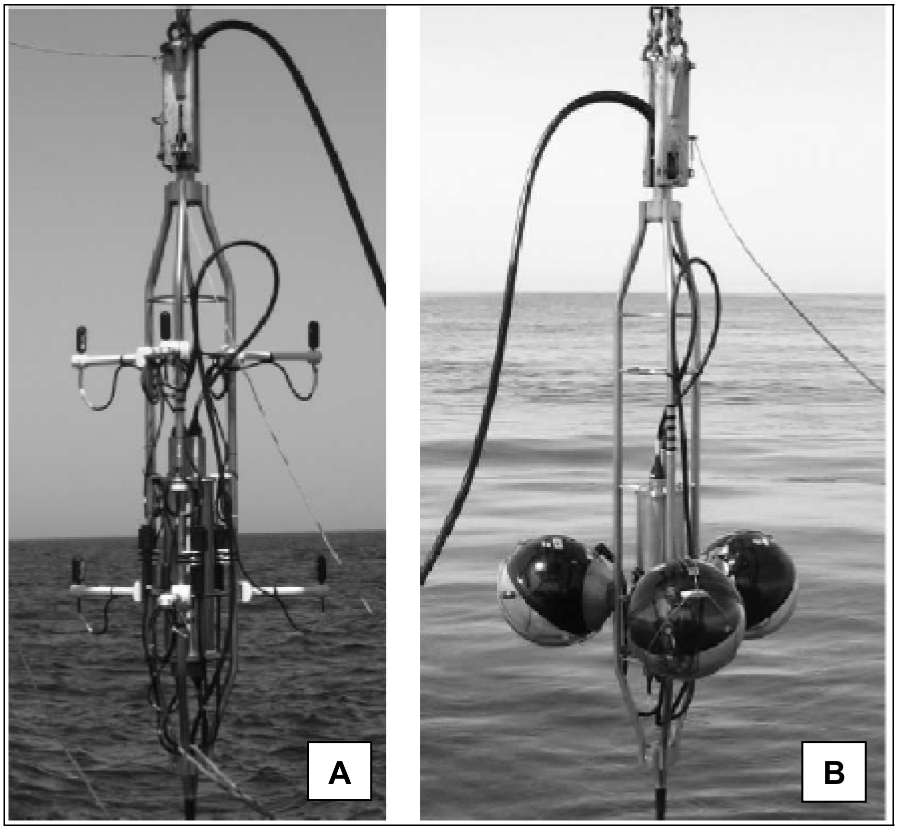

Figure 8A /B. Two types of acoustic 'storeys' used in the ANTARES-AMADEUS observatory:

A) Array of six hydrophones arranged in two vertical stages with equilateral triangle horizontal configurations with the hydrophones are mounted facing upward, thus providing good horizontal and upward looking receiving sensitivity.

B) Acoustic modules consisting of hydrophones mounted inside each of 3 optical spheres (Source: Lahmann et al., 2008).

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A Review of computer-based methods for the automated detection, extraction and classification of marine mammal sounds

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Abstract

Fixed installation, passive acoustic monitoring systems are increasingly being used in the study of marine mammals. These systems typically generate enormous amounts of data which can be costly and time-consuming to review and analyze. Therefore, it is desirable to detect, extract, and classify marine mammal vocalizations using automated or semi-automated methods. In this paper, we review software and other computer-based methods available to accomplish these tasks, outline the gaps in our capabilities and knowledge, and suggest ways forward to fill these gaps. There are several software packages available for detection or classification but few perform both these tasks effectively, and none is able to accurately classify the vocalizations of a large number of marine mammal species concurrently. Methods for the detection and classification of stereotyped baleen whale sounds are relatively well developed, however, efforts are needed which focus on sounds which are more variable, such as odontocete whistles, pulsed sounds, and non-stereotyped baleen whale sounds. Of the methods reviewed, the wavelet transform is an example of one method that has potential for the detection of these types of signals. Tree based models, Gaussian Mixture models, Hidden Markov models and artificial neural networks are among several methods that are promising for use in signal classification tasks, but these need to be tested further and validated using sounds from a larger number of species. Because of the variability in marine mammal sounds, no single method is likely to be effective for automatic detection and classification of sounds for all species and populations. The development of effective, efficient and standardized detection/classification methods for many species will require large, validated data-sets and the acquisition, maintenance and availability of such data-sets will require concerted and organized collaborative efforts. Comparative testing of different methods will require that portions of these large databases contain annotations of validated marine mammal sounds as well as annotations of confounding non-marine mammal sounds. Access to these common datasets and workshops that focus on furthering detection/classification methods are effective ways to address these critically important issues in automated detection and classification of marine mammal sounds.

Key words: automated, detection, classification, feature extraction, marine mammal

1 Introduction

Passive acoustic monitoring (PAM) is a rapidly advancing class of techniques that has the potential to provide data to answer many questions regarding the behavior, ecology and biology and effects of anthropogenic noise on many marine mammal species. Passive acoustic monitoring of marine mammals has advantages over more traditional (e.g., visual) methods because all marine mammals that have been studied to date are known to produce sounds for communication, navigation, and prey detection. In general, sound propagates very efficiently in water. Most marine mammals spend the majority of their time underwater, where they are not available for visual detection or observation. Furthermore, passive acoustic monitoring is effective in most weather, sea state, and light conditions (e.g., day and night), for animals that dive for long periods, and in inaccessible or remote locations (e.g., the deep-sea and ice-covered polar regions). Therefore, it is not surprising that the use of passive acoustic techniques for the detection, identification, and study of marine mammals is becoming standard.

PAM systems can record continuously, be configured to record on a duty cycle (e.g., *x* minutes each hour), or detect only the occurrence of particular types of sounds (automated detection). Even when recording on a duty cycle, these systems can collect huge volumes of data (e.g., gigabytes a day) that can require enormous time and effort to process manually. In order to efficiently process these voluminous data, it is necessary to develop reliable methods for automated detection and classification of sounds produced by marine mammals.

Marine mammals produce sounds that are highly variable with features that span many orders of magnitude along the dimensions of time, frequency, and amplitude. For example, the repertoire of marine mammal acoustic signals includes short-duration (e.g., 2 ms), broadband dolphin echolocation clicks; longer-duration (e.g., fractions of a second to several seconds), mid-frequency tonal dolphin whistles; simple, low frequency fin whale pulses, and long, complex songs of humpback whales that contain components of all of these sound types (e.g., humpback whales). Some species produce distinctive, stereotyped sounds (e.g., blue whales, sperm whales) while others produce signals with great variability (e.g., many dolphin species, humpback and bowhead whales).

The calls of different species often overlap in frequency and time characteristics. For example, the whistles produced by many small delphinid species in the eastern tropical Pacific Ocean have very similar frequency and temporal characteristics and are often detected in the same location at the same time (Oswald et al., 2003). Humpback whales and right whales produce sounds that are very similar on their North Atlantic feeding grounds (R. Sousa-Lima, personal communication, May 30. 2009)

As a result of the high variability and overlapping frequency characteristics for many marine mammal vocalizations, developing effective algorithms to automatically detect, extract feature vectors from, and classify a wide range of acoustic signals can be extremely challenging.

In many cases, even differentiating whether a signal is biological or not biological can be difficult to achieve with certainty. In the past, detection and classification tasks were performed by an experienced bioacoustic analyst who aurally and visually monitored or reviewed recordings and spectrographic displays of sounds (ex. (Oswald et al., 2003; Thompson & Friedl 1982; Clark et al., 1986; Clark & Ellison, 1989; McDonald & Fox 1999, Stafford et al., 1999). The enormous volume of data generated during acoustic surveys makes this review process at best inefficient and at worst impossible to do for many PAM applications.

For decades, scientists have been working to automate these processes. Some of the earliest methods used for automated detection and classification included energy threshold detectors (e.g., Clark, 1980) and matched filters (e.g., Freitag & Tyack, 1993; Stafford et al., 1998). These were used to detect and classify simple, stereotyped sounds produced by species such as blue, and fin whales. For signal classification, multivariate statistical methods can be powerful for sounds produced by species with more variable vocal repertoires (such as dolphins, humpback and bowhead whales) because they can identify complex relationships among many variables. With the advent of more powerful personal computers, the use of multivariate techniques became popular for classifying bird vocalizations in the 1970s and 1980s (e.g., Sparling & Williams, 1978; Martindale 1980a, b). These techniques were soon adopted by marine mammal researchers interested in classifying a variety of marine mammal sounds (e.g., Hafner et al., 1979; Steiner 1981; Clark 1982; Fristrup & Watkins, 1993, Matthews et al., 1999; Rendell et al., 1999). Since this time, enormous effort has been expended on developing these and other automatic methods for the detection and classification of marine mammal species.

The process of automatically detecting and identifying sounds to a particular species or population involves three main steps 1) the detection of a potential sound of interest, 2) the extraction of relevant features from potential sounds of interest, and 3) classification of these sounds (based on the extracted features) as being produced by a marine mammal or a particular species. Here, we review methods and software available to accomplish these three tasks, outline the gaps in our capabilities and suggests ways forward to fill those gaps.

2 Methods

A review of computer automated methods for detection, feature extraction, and classification of marine mammal sounds as well as software packages designed for performing these tasks was conducted by searching the peer-reviewed published literature, gray literature, and the internet. Google, Google Scholar, and bibliographic databases at the University of Hawaii and Scripps Institution of Oceanography (Medline, Biosys, Melvyl, etc.) were searched, and over 300 peer-reviewed publications, book chapters, reports, manuscripts, user manuals, and web pages were compiled and reviewed. Additionally, software and computer algorithm developers were contacted directly via email. Finally, requests for information were sent to the Bioacoustics-L and MARMAM listserves.

3 Results

3.1 Call Detection

Detection of potential acoustic events of interest is the first step necessary in automated analysis of data collected using PAM methods. These potential events of interest then serve as input to a second stage in which events are classified as being a sound event of interest or not. Before computer detection was possible, this was exclusively accomplished by an experienced person who aurally reviewed recordings and/or spectrographic displays of sounds. However, it is often impractical to aurally and visually scan the huge amounts of data collected using these methods searching for marine mammal signals. Therefore it is beneficial to automate this process as much as possible. It is important to note, however, that even when this process has been automated, some aural and visual review is necessary in order to ground truth the detector on the specific data set that it will be used to analyze.

Automated detectors can make two types of errors, missed detections (i.e., missing a sound that exists) and false alarms (i.e., incorrectly detecting a sound that does not exist or is not of biological origin) and these inevitably create a trade-off when choosing the acceptable rate of each. Most detectors allow the user to adjust a threshold, and depending on where this threshold is set, the probability of one of the types of errors will increase while the other decreases. The acceptability of either type of error will be determined by the particular application of the detector. For example, for rare marine mammals in critical habitats, it may be desirable to detect every call, even those that are very faint. In this situation, a low threshold that minimizes the number of missed detections but results in many false detections may be necessary. Quantification of these two error types is a useful way to evaluate the performance of an automated detector.

A common method of conveying the performance of a detector (or classifier) is a confusion matrix, or contingency table. A confusion matrix gives the number of true positives (correctly classified sounds), false positives (or false alarms), true negatives (correct rejections), and false negatives (missed detections) (Figure 1). Another way to visualize the performance of detectors and classifiers is the Receiver Operating Characteristics (ROC) curve. A ROC curve is a two dimensional graph that depicts the trade off between true positives and false alarms (Egan, 1975; Swets et al., 2000). The true positive rate (positives correctly classified/total positives) is plotted on the y-axis and the false positive rate (negatives incorrectly classified/total negatives) is plotted on the x-axis (Figure 2; Fawcett, 2006). A curve is generated by plotting these values for the classifier or detector at different threshold values. The 0,1 point on the graph represents perfect performance – 100% true positives and no false positives.

As mentioned earlier, automated methods for the detection of stereotyped signals of some baleen whales are relatively well developed (Stafford et al., 1998; Mellinger & Clark, 2000), however, the automated detection of more variable calls such as dolphin whistles, non-stereotyped baleen whale calls, and pinniped and sirenian vocalizations requires further development. The following sections describe and evaluate detection methods that are currently being used, or are under development and may fill the gaps in our capabilities.

3.1.1 Energy Threshold Detectors

One of the most common methods for detecting marine mammal calls is to measure the energy or amplitude in a specified frequency band of the incoming signal and determine whether it exceeds a user-determined threshold value. This comparison is usually performed consecutively at each time bin, and the threshold value is typically set relative to the ambient noise in the frequency band of interest (Ura et al., 2004; Ichikawa et al., 2006; Jarvis et al., 2008; Flore et al., 2008; Mellinger, 2008). The first time a signal exceeds the threshold is considered to be the start of a call. Information related to the peak frequency in the current time bin is stored and the next time bin is then examined. The end of the call occurs when no additional peaks exceed the threshold in subsequent time bins. Although a simple and efficient method, the energy threshold detector suffers in signals with low Signal-to-Noise ratios (SNR) as well as in the presence of overlapping signals in the same frequency band from multiple sources. A number of techniques have been devised to overcome these problems, a few of which are described below.

A simple and common method for addressing SNR issues is to filter the incoming signal to reduce or remove ambient noise before any automated detection algorithm is applied (Datta & Sturtivant, 2002; Niezrecki et al., 2003; Mellinger, 2004; Ichikawa et al., 2006; Flore et al., 2008; Gerard et al., 2008; Gillespie & Caillat, 2008; Simard & Roy, 2008).

In the software program *Ishmael* (Mellinger, 2001), it is possible to perform spectrogram equalization to reduce background noise. Equalization is a form of automatic gain control and operates on frequency bands to average out the absolute level of a spectrogram.

Morrissey et al., (2006) implemented N-point FFTs and compared each frequency bin of the FFT output to a time varying threshold. Sperm whale clicks and beaked whale clicks were detected when the number of frequency bins over this threshold exceeded a certain number, typically 10. Detections were classified based on the frequency distribution of the signal (Morrissey et al., 2006; DiMarzio et al., 2008; Marques et al., 2009). A slightly more computationally intensive method of addressing SNR issues involves summing the spectrogram over the frequency bins most likely to contain calls within each time bin. This method reduces interference from background noise and results in calls appearing as larger spikes in spectral sum time series. It is especially effective for impulsive sounds such as sperm whale (*Physeter* *macrocephalus*) clicks and has been used successfully in automated algorithms to detect these sounds (Tieman et al., 2006, Tieman, 2008).

Brandes (2008) and Ward et al. (2008) split the spectrogram into frequency bins and used a different threshold for each band. Thus, bins with higher background noise (typically at low frequencies) could have a higher threshold than bins with little background noise. Ward et al. (2008) achieved an 80% detection rate for high SNR clicks from Blainville's beaked whales (*Mesoplodon densirostris*) using this method. They compared this technique with a linear matched filter detector (see below), and found the matched filter performed significantly better (100% detection rate at very low SNR).

Rather than using a static threshold for energy comparison, Kandia and Stylianou (2008) employed a group delay function to increase detection success even at low SNR. This function uses a time-adaptive system of thresholds related, not to the total energy of a signal, but to the distribution of the signal energy over time. This detector is thus insensitive to variations in sound source levels. The authors achieved a 73% correct detection rate when the algorithm was tested on Blainville's beaked whale clicks.

In order to reduce the risk of classifying an acoustic feature unrelated to the species under investigation, Kandia and Stylianou (2006), Roch et al. (2008), and Soldevilla et al. (2008) applied the Teager energy operator to the feature detected to determine whether or not it was an echolocation click. The Teager operator provides nearly instantaneous energy tracking of a signal by looking at three consecutive signal samples, and tends to emphasize transient signals over noise. Kandia and Stylianou (2006) realized a 94% correct detection rate when this algorithm was applied to the detection of sperm whale clicks.

3.1.2 Entropy Detector

Shannon entropy is a measure of the amount of information contained in a signal. It has been used to characterize and identify animal signals because most animal calls differ from background noise in the peaked-ness of their spectral energy (Tchernichovski et al., 2000; Mellinger & Bradbury, 2007; Valente et al., 2007). Shannon entropy characterizes probability distributions in terms of their degree of peaked-ness, where a strongly peaked distribution is described as having low entropy. Because acoustic power spectral densities (PSDs) are positive additive distributions, they can be treated as probability distributions as long as they are normalized to sum to one (Erbe & King, 2008). A *MATLAB*-based signal detector was developed by Erbe and King (2008) to compute mean PSDs over one minute windows to pre-whiten the data. 'Instantaneous' PSDs are then calculated for 60 ms windows and normalized by the mean PSD. Instantaneous entropy is calculated as the product of the PSD and the logarithm of the PSD. This makes the entropy value calculated independent of total energy. As a result, quiet calls have the same entropy value as loud calls of the same type. For this detector, a call is considered detected when the instantaneous entropy exceeds the median by a threshold times the standard deviation.

The entropy detector outperformed both a simple peak energy detector, and a multi-band energy detector. It worked well for even very faint calls. For example, at a low threshold setting, 168 of 187 (90%) faint signals (SNR <-5dB) were detected and all of the loud signals (n=26, SNR >5dB) were detected. However, there were a large number of false alarms (n=3627). Both the number of detections and the number of false alarms decreased with increasing threshold. False alarms for all three detectors were caused by shipping, distant seismics (e.g., airguns), cable noise, flow noise, and bubbles, with bubbles being the most significant false alarm trigger for the entropy detector.

An additional strength of the entropy detector is that it can process data at speeds considerably faster than real-time. Perhaps the largest advantage of this detector, however, is the fact that it works well on a wide variety of calls. Whereas many detectors are specifically developed to detect one particular species or vocalization, the goal of the entropy detector is to detect signals from as many marine mammal species as possible of those species present in the western Canadian Arctic. For example, this detector was able to detect calls of bowhead whales, beluga whales, and walruses, among others. It is important to note that while the entropy detector performs well with tonal signals (e.g., dolphin whistles) and moans (e.g., bowhead whale calls), it is likely to perform poorly on short, broadband signals such as odontocete clicks.

3.1.3 Page's Test

An alternative technique to determining start and end times of an acoustic signal is Page's test (Ijsselmuide & Beerens 2004; Gerard et al., 2008). Page (1954) developed this procedure to determine the time at which a change occurs in sequentially-obtained data. It is able to minimize the average time delay before detection while constraining the average time between false alarms

(Abraham, 2000). Zimmer et al., (2005) describes the algorithm as follows: given the instantaneous signal magnitude xn, calculate the test variable Vn as

$$V_n = V_{n-1} + \left(\frac{x_n^{\ 2}}{N_n} - b \right),$$

where N_n is a noise estimate and b is the bias for the test variable. A transient is detected when $V_n >$ the detection threshold V_1, and noise is detected when $V_n <$ the noise threshold V_0. Optimal bias and threshold values can be determined by maximizing the detection rate of previously recorded test data signals. This technique is appropriate for species-specific signal detection (e.g., Gerard et al. (2008) detected clicks from Blainville's beaked whales, and calls from Risso's dolphins *(Grampus griseus),* and short-finned pilot whales, *Globicephala macrorhynchus*), as well as detection of 'general' marine mammal vocalizations (Ijsselmuide & Beerens 2004).

3.1.4 Principal Component Analysis/Independent Component Analyisis

La Cour and Linford (2004) applied both Principal Component Analysis (PCA) and Independent Component Analysis (ICA) to the detection of right whale calls. PCA is a simple linear transformation that is used to separate data. ICA is similar to PCA, and separates signals from multiple receivers into multiple non-Gaussian features (in this case, right whale calls) and Gaussian noise. The authors used PCA as a pre-processing step to ICA, and also tested the detection capabilities of the PCA algorithm alone. Signals from multiple receivers were first time-aligned via cross-correlation in order to ensure that a given acoustic feature appeared in the same time window for all receivers. The PCA algorithm was then used to transform the data. The ICA algorithm was applied to a window of fixed length at each time bin, and the resulting statistic was compared to a threshold value to determine if features of interest had been detected. ICA detected approximately 75% of right whale calls with approximately 33% of all calls being false alarms. The authors also found that there was very little difference in detection rate between the PCA-ICA method and PCA alone. Because PCA is approximately 100 times faster, computationally, than ICA, it is much better suited to real-time applications.

3.1.5 Schur Algorithm

The adaptive Schur algorithm is based on the normalized, exact least-square, time-variant lattice filter. It is well-adapted for analysis of non-stationary time-series data (Lopatka et al., 2005a, 2006, 2008). It is applied at every time bin, and the signal is orthogonally projected onto the signal's past values to produce a set of time-varying 'Schur coefficients'. Ambient noise results in constant or only slight variation in these coefficients from one time step to the next, while a non-stationary or transient signal (such as a sperm whale click) produces a drastic change (Lopatka et al., 2006). Lopatka et al., (2006) achieved a 100% detection rate with fewer than 10% false detections when they tested the Schur algorithm on simulated low SNR sperm whale clicks in noise. Detection results may differ, however, when the algorithm is applied to whale signals from real-life recordings with natural and man-made noise.

3.1.6 Wavelet Transform

Although spectrograms are one of the most common methods for representing bio-acoustic signals, they are subject to time-frequency resolution tradeoffs due to the uncertainty principle. This principle states that it is impossible to know both the exact frequency and the exact time of occurrence of that frequency in a signal. In other words, a signal can not be represented as an exact point in time-frequency space, and increasing the resolution of one will decrease the resolution of the other. The wavelet transform is one technique developed to overcome this limitation. In wavelet analysis the spectrum of the signal is calculated with a fully scalable, modulated window (like a constant Q filter bank), as opposed to a fixed window as used in Fourier transforms. Spectrum generation is repeated many times with different-sized windows, resulting in a collection of time-frequency representations of the signal with different resolutions. In general, higher frequencies are better resolved in time, and lower frequencies are better resolved in frequency (Burrus et al., 1998).

The wavelet transform is continuously applied to the incoming signal. One advantage of this method is that the coefficients of the algorithm can be used to substantially reduce noise, which makes the wavelet transform very robust for signal detection in noisy data (Adam et al., 2005). For example, Lopatka et al., (2005b) found the wavelet transform to be superior to an energy detector when tested on sperm whale clicks resulting in a 97% detection rate and a 4.5% false alarm rate.

Many different wavelet transforms have been developed, and selection of an appropriate transform is often accomplished through optimization of test data. One form of wavelet transform, the Overcomplete Wavelet Transform (OCWT), was developed to mimic the physical phenomena behind the human auditory system to highlight calls of interest in the incoming signal (Ioana et al., 2006). The OCWT can be thought of as a linear filter bank spanning the frequency range of interest. Once the signal has passed through the OCWT and has been divided into multiple sub-bands, a split-and-merge algorithm is used to combine regions where calls have been detected and discard the rest. When tested on bottlenose dolphin (*Tursiops truncatus*) whistles, this technique outperformed an energy detector and was able to detect signals even when the SNR was close to 0 dB (Ioana et al., 2006). It is well-suited for real-time detection, as it is completely adaptive and requires no prior information about the received signal. There is only one parameter to set – the confidence interval. This is one of the more promising methods for the detection of tonal signals such as dolphin whistles and would probably also work well for variable calls produced by baleen whale species such as humpback whales, bowhead and right whales.

3.2 Feature Vectors

When developing methods for automated detection and classification, the features used as input to the algorithms must be considered. A wide variety of parameters (i.e. features) can be measured (or extracted) from signals. The feature-set that is selected, and the accuracy with which the measurements are taken, have a significant influence on the success (or failure) of a classification algorithm. Feature sets should provide as much information as possible, but these features must be chosen carefully because the amount of training data necessary increases with the dimensionality of the data. The choice and validation of feature sets is a time-consuming and laborious process, but is crucial when developing classification systems. Once the features have been selected, automating extraction and subsequent analysis of these features reduces subjectivity and the time required to analyze the huge data sets collected using fixed PAM techniques.

Many researchers have written feature extraction algorithms, but very few are available for widespread or public use. Unfortunately, feature extraction is rarely the focus of published literature, and as such is often only mentioned in passing with very few details of the methods used. There are many different methods for feature detection and extraction, as well as numerous variations within methods. Common feature vectors and extraction techniques are described here, with success rates specified when known.

3.2.1 Spectrographic Features

Perhaps the most commonly used feature vectors are those containing parameter values measured from spectrograms. There are many spectrographic features that can be easily measured from marine mammal vocalizations. These include, but are not limited to frequency variables such as beginning, ending, peak, center, and bandwidth; and time variables such as signal and sub-signal duration, phrase and song length (e.g. humpback whale songs) and inter-call intervals. These variables are usually simple to measure and automate. More complex features such as those describing the spectrographic 'shape' of a vocalization (slopes, number and relative position of inflection points, etc.) have also been used (Clark, 1982; Chabot,1988;, Fristrup & Watkins, 1993). These measurements are often made manually from spectrographic displays (e.g., by a technician using a mouse-controlled cursor or pointer), but this process can be subjective and dependant upon spectrographic settings used (e.g., FFT-size, the type of window used, and percent overlap). Automated techniques for extracting spectrographic measurements can be affected by the same factors, but are less subjective and time consuming.

3.2.1.1 Peak Frequency Tracing — This method applies to tonal signals such as dolphin whistles and some baleen whale calls (e.g., tonal calls of bowhead, humpback and blue whales). Once a signal of interest has been detected, the frequency contour must be extracted in order to generate the feature vector. The most general method of contour extraction is to combine, into a single contour, frequencies in consecutive time bins with energy above a user-defined threshold. These frequency peaks occur within a user-defined frequency band and amplitude range of each other (Buck & Tyack, 1993; Datta & Sturtivant, 2002; Bjorgesaeter et al., 2004,; Halkias & Ellis, 2006; Oswald et al., 2007; Brandes, 2008; Madhusudhana et al., 2008). Difficulties can arise when multiple peaks in a single time bin can be linked to the same peak in the preceding time bin (such as when there are overlapping signals). Additional criteria are then often applied to improve the contour extraction. These include examination of the contour slope (Halkias & Ellis, 2006; 82% extraction success rate), species-specific rules, and heuristics (Madhusudhana et al., 2008, resulting in a 90% extraction success rate). Instead of focusing solely on the peak with the highest energy in the current time bin, many schemes keep track of multiple peaks in order to allow extraction of overlapping signals (Halkias & Ellis, 2006; Brandes, 2008). Peak tracing has been successfully applied to dolphin whistles (Buck & Tyack, 1993, Datta & Sturtivant 2002;

Halkias & Ellis 2006; Oswald et al., 2007) and blue whale calls (Madsudhana et al., 2008), as well as vocalizations produced by many terrestrial species such as birds, crickets and frogs (Brandes 2008)

3.2.1.2 Curve Fitting -- Matthews (2004) separated incoming signals into short segments and then computed linear models of the signals within those portions using a maximum likelihood estimator. Contiguous models which did not differ in frequency by more than some upper limit were then recombined into a full contour, and the parameters of the linear models were used as the feature vector. This method can only detect a single signal in each time frame, and is therefore unable to analyze data that include overlapping signals. Because the technique is applied sequentially to only short segments of the signal, it does not perform as well during periods with low signal-to-noise-ratio (SNR). Furthermore, long signals may inappropriately be broken up into several shorter ones. Although not optimal for application to longer signals, this method did show potential when applied to short upsweeps produced by right whales (Matthews, 2004). Datta and Sturtivant (2002) employed a least-squares fitting routine to describe the shape of the contour, and then used information from the resulting equations to create a feature vector for common dolphin whistles.

3.2.2 Other Features

Although spectrographic features have been used most commonly, there are a host of other types of features that can be extracted from marine mammal vocalizations and used for species identification. Some examples of these are provided below.

3.2.2.1 Capon's Minimal-Variance -- Spectral Estimator / Watershed Method --

Leprettre and Martin (2002) used Capon's minimal-variance spectral estimator to create a time-frequency representation (TFR) of the incoming signal similar to a spectrogram, but without the same limitations (see previous discussion of the uncertainty principle in Wavelet Transform). Originally developed for wave-number estimation in array signal processing (Capon, 1969), the technique measures the power out of a set of uniform narrow-band filters to adapt to the signal and reduce the response of spectral components outside the band of interest (Martin et al., 1995). After the Capon estimation, Leprettre and Martin (2002) used a priori knowledge of the desired marine mammal call to design a criterion to distinguish between calls and surrounding background noise. Based on this criterion, a second transform was developed and applied to the TFR to highlight the boundaries between the marine mammal calls and the background noise. Possible transforms include the modulus of morphological gradient, Top-Hat transforms, erosions, dilations, etc. (Serra, 1982). The watershed method, an algorithm which performs boundary detection on each point in a 2D array (Vincent & Soille. 1991), is then applied to extract contours by following the local maxima in the call. This method produced relatively good results when applied to dolphin whistles and allows extraction of contours with differing power levels over time. However, it requires prior knowledge of the signal and, therefore, is limited in its use for feature extraction of variable signals or of signals produced by multiple species.

3.2.2.2 Warping-Based Signal Decomposition -- Ioana et al., (2006) developed the Warping-based Signal Decomposition (WSD) method for analysis of the time-frequency representation of signals with non-linear time-frequency structure. Cetacean calls are generally non-linear, and this poses a problem for typical time-frequency analysis. The WSD technique proposed by the authors first linearized the non-linear time-frequency structures through a battery of warping operators, and then extracted relevant parameters for the most representative time-frequency structures describing the call of interest. The time-frequency representation created by Ioana et al., (2006) is not limited to the time-frequency resolution tradeoffs due to the uncertainty principle that spectrograms are bound by and, therefore, results in much more precise signal parameters. This method performed well when applied to the signals of bottlenose dolphins, pilot whales, and common dolphins and was also relatively robust to noise.

3.2.2.3 Particle Filter -- White and Hadley (2008) analyzed the short-time fractional Fourier transform (STFrFT), which can be conceptualized as representing the energy in a signal at a particular time and frequency associated with a particular sweep rate. The classic spectrogram is a special case of the STFrFT, in which the sweep rate is ignored. By including the sweep rate in the algorithm, the STFrFT is able to increase the SNR of a signal (as long as the chosen sweep rate is close to the actual sweep rate inherent in marine mammal calls). The authors used Sequential Importance Resampling to extract contours of delphinid whistles. The Sequential

Importance Resampling is a particle filter which infers the signal parameters by recursively subjecting samples of noisy incoming signal to Monte Carlo algorithms and adjusting likelihood modifiers accordingly. While quite successful in extracting the sample whistle shown in the literature, the authors note that the method is 'computationally expensive' and would require modification to optimize it for real-time implementation.

3.2.2.4 Cepstral Features -- Cepstral coefficients are spectral features of bio-acoustic signals commonly used in human speech processing (Davis & Mermelstein, 1980). They are well suited for statistical pattern recognition models because cepstral coefficients tend to be uncorrelated with each other (Clemins et al., 2005). This significantly reduces the number of parameters that must be estimated (Picone, 1993). Cepstral features are calculated by computing the Fast Fourier Transform of each window of a sound. The frequency axis is then warped by multiplying the spectrum with a series of n filters at appropriately spaced frequencies. The discrete cosine transform of the log filterband output results in an n dimensional cepstral feature vector (Picone, 1993; Clemins et al., 2005; Roch et al., 2007; 2008).

Using cepstral feature space allows the timbre of sounds to be captured, a quality that is lost when extracting parameters from spectrograms (Roch et al., 2007). Roch et al. (2007) developed an automated system based on cepstral feature vectors extracted from whistles, burst pulses, and clicks produced by short- and long-beaked common dolphins, Pacific white-sided dolphins, and bottlenose dolphins. This system does not rely on specific call types and has no requirement for separating individual calls. The system performed well, with correct classification scores of 65-75% depending on the partitioning of the training and test data. Roch et al. (2008) showed that cepstral feature vectors can be used as the basis of automated detectors for echolocating marine mammals, and Muoy et al. (2008) used cepstral features in their GMMs for classifying vocalizations of six species recorded in the Chukchi Sea. Both of these studies reported low error rates. For example, Roch et al. (2008) showed that equal error rates (the point at which a decision threshold results in the same percentage of false alarms and missed detections) ranged from 0.03% to 16.8%. Muoy et al. (2008) presented classification results in the form of Classification Operating Characteristic curves (similar to ROC curves) for each species tested and therefore specific error rates are not reported here. Cepstral features appear to be a promising alternative to the traditional time and frequency parameters measured from spectrograms and input to classification algorithms. It is important to note, however, that cepstral features are relatively sensitive to the SNR of the signal, the phase, and the modeling order (Ghosh et al., 1992).

3.2.2.5 Generalized Perceptual Linear Prediction Model -- The generalized perceptual linear prediction model (gPLP) for feature extraction developed by Clemins and Johnson (2006) incorporates information about the perceptual abilities and vocal tract characteristics (or air sacs in marine mammals) of the species under study to calculate relevant features. It is based on the perceptual linear prediction (PLP) model developed by Hermansky (1990) for human speech. The first step in the feature extraction process is to filter the vocalization using a 'pre-emphasis' filter that reduces the dynamic range of the spectrum so that it is more easily approximated by the autoregressive modeling step of the analysis. The vocalization is then broken into frames and windowed and the power spectrum is estimated. This power spectrum is transformed to account for several psychoacoustic phenomena. First, a triangular filter bank is applied to the power spectrum to account for both critical band frequency masking and the nonlinear mapping between cochlear position and frequency sensitivity. A simple triangular filter shape is used because little data are available on the auditory filter shapes of animals other than humans. Once the filter bank energies have been calculated, an equal-loudness curve (approximated from the audiogram of a species) is used to normalize them (Clemins & Johnson 2006, Clemins et al., 2006). To account for the relationship between the actual intensity of a sound and its perceived loudness, the 'intensity-loudness power law' is then applied. Finally, autoregressive modeling takes place. In this step the normalized filter bank energies are approximated by an all-pole model using the autocorrelation method and the Yule-Walker equations (Makhoul, 1975). The coefficients generated during this step are transformed into the cepstral domain using a recursive formula (Deller et al., 1993). These final gPLP coefficients are largely uncorrelated and represent the shape of the vocal tract filter during vocalization production. This results in feature vectors that take the perceptual abilities of the species into account (Clemins et al., 2006). Many of the transformations used to obtain these coefficients are based on human data, but they have been shown to be an effective feature vector for the individual classification of mammals and birds such as African elephant (*Loxodonta africana*) rumbles, ortolan bunting (*Emberiza* *hortulana*) song-type classification and singer identification, and for the classification of beluga whale whistles (Clemins & Johnson, 2006; Clemins et al., 2006).

3.3. Classification

Classification of bio-acoustic signals such as some whale, pinniped and sirenian vocalizations, and dolphin whistles and clicks is a problem that has been challenging researchers for decades. For example, dolphin whistles are highly variable both within individuals and within species, and clicks can also show significant variation due to different propagation paths or orientations of animals. The frequencies utilized by different species of marine mammals overlaps markedly and many species produce sounds with very similar frequency contours (e.g., striped, common, and spinner dolphins; humpback and bowhead whales). In addition, marine mammals often produce overlapping vocalizations, making it difficult to pull out individual sounds for analysis. These factors make many marine mammals difficult to classify to species acoustically. In addition, there are natural and anthropogenic noises and signals that can interfere or be easily confused with marine mammal sounds (e.g., military sonar, mechanical and engine sounds, oil and gas exploration and production).

Several promising methods for the classification of marine mammal sounds are currently being developed and explored by researchers. Some of these will be described in the following sections. When examining the results outlined in these sections, it is important to compare classifier performance to what would be expected by chance alone (ex. 33% for three species, 12.5% for 8 species, etc.).

3.3.1 Multivariate Discriminant Function Analysis

Multivariate discriminant function analysis (DFA) is a parametric statistical technique dating back to at least 1935 (Fisher, 1936; Afifi & Clark, 1996). This technique determines linear combinations of measured variables that best characterize the differences among groups. These linear combinations are known as 'canonical discriminant functions'. The first canonical discriminant function is the linear combination of variables that maximizes the differences among the means of the groups in one dimension. The second canonical variable represents the maximum separation of the means in a direction that is orthogonal to the first, the third canonical variable represents the dispersion in a dimension independent of the first two, and so on (SPSS, 1997). In DFA analysis, variables can be entered into the analysis all at the same time, or in a stepwise fashion (either forwards or backwards). When canonical discriminant functions have been calculated, variables measured from individuals in the test data-set are then substituted into each function and individuals are classified according to the function that produced the highest result. Because DFA is a parametric technique, it is assumed that the data used have a multivariate, normal distribution with the same covariance matrix (Afifi & Clark, 1996). Violations of these assumptions can create problems with some datasets. The main weakness of DFA for marine mammal classification tasks is that it assumes classes are 'linearly separable'. Because a linear combination of variables takes place in this analysis, the feature space can only be separated in certain, restricted ways that may not be appropriate for all marine mammal vocalizations.

Discriminant function analysis is, however, a commonly used and understood statistical tool and, as a result, it is available in many frequently used commercial statistical software packages (e.g., *BMDP, SAS, SPSS, STATISTICA*, and *SYSTAT*). *MATLAB* also includes DFA in its statistics toolbox add-on. This makes DFA an accessible classification tool for many researchers. Perhaps for this reason, DFA has been one of the more commonly employed methods for the classification of marine mammal vocalizations.

Table 1 lists species, variables measured, and correct classification scores for marine mammal classification studies that used DFA. Correct classification scores ranged from 28% for 10 species (Matthews et al., 1999) to 70% for five species (Steiner, 1981). Overall correct classification scores in most of these studies were significantly greater than would be expected by chance alone. Similar variables were measured from spectrograms for most of these studies (with the exception of Fristrup & Watkins, 1993 and Gillespie & Caillat, 2008). It is possible that the performance of DFA could be improved with the use of different or additional variables. This possibility should be examined in future research. Another technique that may serve to improve classification results is to base classification decisions on the output of more than one classification algorithm. Oswald et al. 2007 based classification decisions on a combination of DFA and classification trees, a strategy which increased correct classification by 11% over using DFA alone (see Table 1).

3.3.2 Artificial Neural Networks

Artificial neural networks (ANNs) were developed by modeling biological systems of information processing (Deecke et al., 1999) and became very popular in the areas of word recognition (e.g., Waibel et al., 1989; Lefebvre et al., 1990; Gemello & Mana 1991) and character or image recognition (e.g., Van Allen et al., 1990; Fukushima & Wake 1990; Belliustin et al., 1991) in the 1980s. Since that time, ANNs have been successful at classifying a number of complex signal types, including human speech (Huang & Kuh 1992), dolphin echolocation signals (Au & Nachtigall 1995, Roitblat et al., 1989), quail crows (Deregnaucourt et al., 2001), alarm calls of prairie dogs (Placer & Slobodchikoff 2000), and stress calls of domestic pigs (Schon et al., 2001).

There are 20 or more basic architectures of ANNs, including: back-propagation classifiers, feature-map classifiers, LVQ classifiers, radial basis function classifiers, Boltzmann machines, and modified nearest neighbor approaches (see Lippman (1989) for a review of these and other ANNs). Each ANN approach provides trade-offs in their memory and computation requirements, training complexity and time and ease of implementation and adaptation (Lippman, 1989). The choice of ANN depends on the type of problem to be solved and the resources available.

All ANNs are composed of units, called ‘neurons’, and the connections between them. They typically consist of three or more neuron layers: one input layer, one output layer, and one or more hidden layers (Figure 3). The input layer consists of *n* neurons that code for *n* features in the feature vector representing the signal ($X_1 \ldots X_n$). The output layer consists of *k* neurons representing the *k* classes. The numbers of hidden layers between the input and output layer, as well as the number of neurons per layer, are empirically chosen by the researcher. Each connection between neurons in the network is associated with a weight value which is modified by successive iterations during the training of the network. In the hidden and output layers, the state of the signal from the previous layer is evaluated according to:

$$a_j = \sum_{i=1}^{I} X_i W_{ji} \ ,$$

where a_j is the net input of neuron *j*; X_i is the output value of neuron *i* of the previous layer; and W_{ji} is the weight factor of the connection between neuron *i* and neuron *j* (Reby et al., 1997). An ANN is initialized with random weights and trained by cycling through all training examples and then correcting the weights to minimize the error between the observed and the expected outputs (Potter et al., 1994). For example, back propagation networks, one of the most frequently used architectures, are trained by modifying connection weights to minimize the sum squared error of the reply. The adjustment of weights, layer by layer, is calculated from the output layer back to the input layer (Reby et al., 1997).

ANNs are promising for automatic signal classification for several reasons. First, the input to an ANN can range from feature vectors of measurements taken from spectrograms or waveforms, to frequency contours, to complete spectrograms. Analyses based on frequency contours or spectrograms, in contrast to isolated measurements taken from spectrograms, require little or no prior knowledge as to where differences among signals may exist. As a result, subtle and localized differences that may be missed by taking measurements of a limited number of user-selected variables may be detected when using frequency contours or spectrograms (Deecke et al., 1999). It is important to note, however, that the time-frequency tradeoff inherent to spectrograms can dramatically affect the representation of a signal and how it is classified. For example, very different spectrograms can be produced from the same signal by making only slight changes in window size of the FFT (Murray et al., 1998). Caution should be taken, therefore, when using spectrograms as input to ANNs. Second, ANNs serve as adaptive classifiers that learn through examples. As a result, it is not necessary to develop a good mathematical model for the underlying signal characteristics before analysis even begins (Ghosh et al., 1992). In addition, ANNs are non-linear estimators. This means that they are well-suited for problems involving arbitrary distributions and noisy input (Ghosh et al., 1992, Potter et al., 1994).

A commonly cited drawback to ANNs is that they are a 'black box' and, therefore, it is difficult to determine exactly how they are making classification decisions. However, Potter et al. (1994) were able to investigate the roles of hidden neurons by linearizing the transfer functions. Using this technique, they were able to 'interrogate' their ANNs to reveal their operating paradigms and confirm that they were classifying based on relevant features.

The performance of ANNs varies according to the type of architecture, the number of hidden layers and neurons, and the amount of training data. For example, if there are too few neurons, the ANN will not perform well on either training or novel data. If there are too many neurons, on the other hand, the ANN may be over-fit to the training dataset, and will not generalize well to novel or slightly different real-life data (Potter et al., 1994). Most of the ANNs used to classify marine mammal calls have performed well and, when compared to other classification techniques, yielded the better results. For example, Potter et al., (1994) used a feed-forward, back-propagation-trained ANN to classify bowhead whale end notes and interfering noises (such as bearded seals, *Erignathus barbatus*, beluga whales, ice, wind, and wave noise). Spectrograms were used as input features. Their ANN produced a minimum error rate of 1.5% vs. a spectrogram correlator, which had an error rate of 3.6%. Deecke et al. (1999) used a standard back-propagation ANN to categorize killer whale dialects to nine matrilineal groups. Input to this ANN consisted of pulse-rate contours plus call length. Their ANN was successful, giving similar results to those obtained when humans categorized the same sounds. Dolphin echolocation clicks were classified into seven categories defined by peak frequency and bandwidth information using a counter-propagation network by Houser et al. (1999). Their correct classification scores ranged from 45.5% to 82% for clicks produced by different individual dolphins. Elsberry (2003) used a modified version of Houser et al.'s classification scheme to classify bottlenose dolphin echolocation clicks. Elsberry's method restricted the number of data points for spectral analysis to those computed to be within the click duration, in contrast to the fixed 256 samples used by Houser et al., (1999). This modification made the algorithm less sensitive to noise. A feed-forward network trained with back-propagation was used by Seekings and Potter (2003) to classify humpback whale song units into 17 classes, resulting in a correct classification score of 86%. Feature vectors in this study were created using wavelet packet decompositions. Finally, Mellinger (2008) also used a feed-forward ANN trained using back-propagation to classify clicks as Blainville's beaked whales, or 'other'. Conditioned spectrograms (equalized, rectified, and normalized) were used as input to the ANN. At the 99% correct classification rate, only 0.6% of beaked whale clicks were missed. Mellinger postulated that one reason for the very good performance of this classifier is that the training and testing data were drawn from the same recordings, and therefore likely the same whales. The signals to be detected were therefore probably very similar between the training and testing sets. Nevertheless, the good results produced using ANNs in this and the other studies listed suggest that ANNs are a promising tool for the classification of acoustic signals from many species of marine mammal.

3.3.3 Classification Tree Analysis

Classification tree analysis is a non-parametric statistical technique that recursively partitions data into groups known as 'nodes' through a series of binary splits of the dataset (Clark & Pregibon, 1992; Breiman

$$\text{Deviance} = -2\sum_{k=1}^{N} y_{ik} \log(p_{ik}) \text{ ,}$$

where $y_{ik} = 1$ if the k^{th} individual is of class i and $y_{ik} = 0$ otherwise, p_{ik} = the probability that the k^{th} individual is of class i (estimated as the fraction of individuals in the node of class i). Each node is split so as to maximize the deviance between the two resulting nodes (Fristrup et al., 1984). Each split is based on a value for a single variable and the criteria for making splits are known as 'primary splitting rules'. The 'deviance', a measure of diversity, is calculated at each node:

$$\text{Deviance} = -2\sum_{k=1}^{N} y_{ik} \log(p_{ik}) \text{ ,}$$

where $y_{ik} = 1$ if the k^{th} individual is of class i and $y_{ik} = 0$ otherwise, p_{ik} = the probability that the k^{th} individual is of class i (estimated as the fraction of individuals in the node of class i). Each node is split so as to maximize the deviance between the two resulting nodes (Fristrup and& Watkins; 1993). Splitting results in successively 'purer' nodes and continues until each node contains perfectly homogeneous data (Gillespie & Caillat, 2008). When this maximal tree has been grown, it is then 'pruned' by removing nodes and examining the error rates of these smaller trees. The smallest tree with the highest predictive accuracy is considered to be the 'optimal tree' (Oswald et al., 2003). Figure 3 provides an example of a classification tree used to classify the whistles of nine delphinid species.

Tree based analysis provides several advantages over other classification techniques. It is a non-parametric technique; therefore, data do not need to be normally distributed as required for some methods such as DFA. In addition, tree based analysis is a simple and naturally intuitive way for humans to classify sounds. It is essentially a series of true/false questions, which makes the classification process transparent, unlike other 'black box' techniques such as neural networks in which the process is hidden to the user. This allows easy examination of which variables are most important in the classification process. Tree based analysis also accommodates for a high degree of diversity within classes. For example, if a species produces two or more distinct call types, a tree-based analysis can create two different nodes to account for this. In other classification techniques, different call types within a species simply act to increase variability and make classification more difficult. Finally, 'surrogate splitters' are provided at each node (Oswald et al., 2003). Surrogate splitters closely mimic the action of primary splitting rules and can be used in cases when the primary splitting variable is missing. As a result, calls can be classified even if data for some variables are missing due to noise or other factors.

Classification trees have been applied to marine mammal sounds by several researchers, with promising results, although there is still room for further improvement. Fristrup and Watkins (1993) used tree-based analysis to classify the calls of 53 species of marine mammal (including odontocetes, mysticetes, pinnipeds and manatees). Their correct classification score of 66% was 16% higher than the score obtained when applying DFA to the same dataset. The whistles of nine delphinid species were correctly classified 53% of the time by Oswald et al., (2003) using tree-based analysis. Oswald et al. (2007) subsequently applied classification tree analysis to the whistles of seven species and one genus, resulting in a correct classification score of 41%. This score was improved slightly, to 46%, when classification decisions were based on a combination of classification tree and DFA results. Finally, Gillespie and Caillat (2008) classified the clicks of Blainville's beaked whales, short-finned pilot whales, and Risso's dolphins. Their tree-based analysis classified 80% of clicks to the correct species. The variables that were used in each of these studies are the same as those listed in Table 1 for DFA analyses.

3.3.4 Gaussian Mixture Models

Gaussian Mixture Models (GMMs) are commonly used to model arbitrary distributions as linear combinations of parametric distributions. They are appropriate for species identification when there is no expectation as to the sequence of calls and when multiple calls may occur simultaneously (Roch et al., 2007). To create a GMM, a set of N normal distributions with separate means and diagonal covariance matrices are scaled by weight factors, c_i ($1 \leq i \leq N$). The sum of the c_i's must be one to ensure that the GMM represents a probability distribution (Huang et al., 2001; Roch et al., 2007, 2008). The number of mixtures in the GMM is chosen empirically and its parameters are estimated using an iterative algorithm such as the expectation maximization (EM) algorithm (Moon, 1996). Once a GMM has been trained, likelihood is computed for each call, or group of calls and a log-likelihood ratio test is used to decide which species it belongs to (Roch et al., 2008). Gaussian Mixture Models can be implemented using the Hidden Markov Model Toolkit (HTK) by Young et al. (2002) (from Roch et al.(2007)), which is an open source suite of software programs designed for human speech recognition.

Roch et al. (2007) used GMMs and cepstral feature vectors to classify whistles, clicks and burst pulses produced by common dolphins (Delphinus delphis and Delphinus capensis), Pacific white-sided dolphins (Lagenorhynchus obliquidens), and bottlenose dolphins recorded in the southern California Bight and the Gulf of California, with 67-75% correct classification depending upon the partitioning of training and test data and the number of mixtures used. In a later study, Roche et al. (2008) classified clicks produced by Blainville's beaked whales, pilot whales, and Risso's dolphins using a GMM. Correct classification scores for these three species were 96.7%, 83.2%, and 99.9%, respectively. Brown and Smaragdis (2008, 2009) used GMMs to classify calls of killer whales (*Orcinus orca*), resulting in up to 92% agreement with perceptually created categories of call types (n=75), depending on the number of cepstral coefficients and Gaussians in the estimate of the probability density function. GMMs have also been used successfully to classify the A and B type calls produced by blue whales in the NE Pacific (McLaughlin et al., 2008), and six species recorded in the Chukchi Sea (beluga whales, Delphinapterus leucas, bowhead whales, killer whales, humpback whales and gray whales, as well as walruses, Odobenus rosmarus, (Mouy et al., 2008). Muoy et al. (2008) tested two types of feature vectors – cepstral coefficients and wavelets, with cepstral coefficients having a higher success rate. Both of these studies reported that their classifiers worked very well, but correct classification scores were not provided. In general, GMMs seem to be a very promising technique for classifying marine mammal acoustic signals.

3.3.5 Support Vector Machines

Support Vector Machines (SVMs) are a rich family of 'learning algorithms' based on Vapnik and Chervonenkis' work in statistical learning theory. According to statistical learning theory, the best classifier is the one that minimizes both the training error and the complexity of the classifier (Cristianini & Taylor 2000; Mazhar et al., 2007). In accordance with this idea, SVMs find the optimal hyper-plane between two classes that maximizes the separation between the classes and has the lowest risk of error. The optimal hyper-plane can be represented by:

$$\vec{w} \cdot \vec{x} + b = 0 \, ,$$

where $\vec{w}$ is a weight vector, and b represents bias. Correctly classified examples in the training set $\Im = \{(x_i, d_i)\}_{i=1}^{N}$ can be described by the inequality $d_i(\vec{w} \cdot \vec{x} + b) - 1 \geq 0$ for all *i,* and training data satisfying this condition are called support vectors. A SVM finds the optimum values of the weight vector, $\vec{w}$, and bias, *b,* using the training sample $\Im = \{(x_i, d_i)\}_{i=1}^{N}$ so that the weight vector minimizes the cost function:

$$\Phi(\vec{w}, \vec{\xi}) = \frac{1}{2} \vec{w}^T \vec{w} + C \sum_{i=1}^{N} \xi_i \, ,$$

where ξ is a slack variable and C is a penalty parameter. The slack variable accommodates for data points that fall on the 'wrong' side of the hyper-plane (Mazhar et al., 2000). A larger ξ corresponds to more rigid separation of classes and less tolerance for class overlap in the training data (Jarvis et al., 2006). The penalty parameter assigns cost to errors in classification and is determined experimentally using training data (Mazhar et al., 2000).

SVMs were originally designed for binary classification, but a number of methods have been developed for applying them to multi-class problems. The three most common methods are as follows: 1) form *k* binary 'one-against-the-rest' classifiers (where *k* is the number of classes) and choose the class whose decision function is maximized (Vapnik, 1998), 2) form all *k*(*k*-1)/2 pair-wise binary classifiers and choose the class whose pair-wise decision functions are maximized (Li et al., 2002), and 3) reformulate the objective function of the SVM for the multi-class case such that the decision boundaries for all classes are optimized jointly (Guemeur et al., 2000).

Jarvis et al., (2006) developed a new type of multi-class SVM called the class-specific SVM (CS-SVM). In this method, *k* binary SVMs are created, where each SVM discriminates between one of the *k* classes of interest and a common reference class. The class whose decision function is maximized with respect to the reference class is selected. If all decision functions are negative, the reference class is selected. The advantage of this method is that noise in recordings is treated as the reference class. Jarvis et al. (2006) used their CS-SVM to discriminate clicks produced by Blainville's beaked whales from ambient noise and obtained a correct classification score of 98.5%. They also created a multi-class CS-SVM that classified clicks produced by Blainville's beaked whales, spotted dolphins and man-made tracking pings. This CS-SVM resulted in 98% correct classification for Blainville's beaked whale clicks, 88% correct classification for spotted dolphin clicks, and 95% correct classification for tracking pings. It is important to note that their training data was included in their test data, which likely resulted in inflated correct classification scores. Times between the first several consecutive zero-crossings on the waveforms were used as feature vectors in both of these examples.

Mazhar et al. (2007) used a multi-class SVM and cepstral coefficient feature vectors for the recognition of calls produced by seven individual humpback whales. Their SVM resulted in 99% correct classification, which was a significant improvement over the 88% correct classification obtained using a GMM on the same dataset (Luan et al., 2003). SVMs have several advantages over GMMs. First, the improvement seen by Mazhar et al., (2007) was obtained with a highly reduced training dataset size. In addition, GMMs depend heavily on accurate calculation of clusters for generating proper models and the selection of initial parameters has a significant influence on the clustering result. SVMs are not bound by these constraints. Based on the two studies that have tested SVMs, they seem to have potential for species identification, but they need to be tested on a larger number of species and in different SNR situations. Mazhar et al., (2007) used recordings with a high SNR, which likely contributed to the high correct classification scores they obtained. Additionally, because SVMs are essentially binary classifiers, it is questionable as to whether they will be useful for classification problems involving a large number of species.

3.3.6 Spectral Peaks and Notches

Soldevilla et al. (2008) examined the potential for using spectral peaks and notches to classify echolocation clicks produced by wild dolphins in the southern California Bight. They examined clicks produced by five delphinid species commonly observed in the area (short- and long-beaked common dolphins, bottlenose dolphins, Pacific white-sided dolphins, and Risso's dolphins), and quantified spectral peaks and notches using a first-order regression-based peak and notch selection algorithm on normalized click spectra created using series of concatenated clicks. Echolocation clicks are directional and their waveform and spectral characteristics have been shown to change considerably with orientation relative to a hydrophone (Au, 1993). Nevertheless, Soldevilla et al. (2008) discovered consistent spectral characteristics in clicks recorded from groups of Risso's and Pacific white-sided dolphins. However, consistent spectral patterns were not found in the clicks of common or bottlenose dolphins. This suggests that classification decisions can be based on the spectral characteristics of clicks for only some species. For delphinids, it is probably necessary to include all vocalization types into species identification algorithms. Soldevilla et al. (2008) are currently working on automated classifiers that include both clicks and whistles.

3.4. Combined Detection/Extraction/Classification Techniques

Several methods have been developed that perform multiple functions in the detection, extraction and classification sequence. Some, like the Hilbert-Huang transform and the adaptive notch filter, perform both detection and contour extraction. Others, such as spectrogram correlation and matched filters detect specific calls and are therefore performing detection and classification at the same time. Using combined methods is generally faster and more efficient than using a two or three step process. However, many of these methods are useful only for certain types of signals, such as stereotyped calls produced by some baleen whales. A few of these methods are reviewed below.

3.4.1 Detection/Feature Extraction

3.4.1.1 Hilbert-Huang Transform – Adam (2006, 2008) used the Hilbert-Huang transform (HHT) as an alternative to the traditional spectrogram. There are two steps to the HHT. The first step is empirical mode decomposition (EMD): mono-component contributions (intrinsic mode functions, or IMFs) to the signal are extracted based on localization of their extrema. All signal components are divided between all the IMFs according to their instantaneous frequency. In contrast to wavelet analysis (see above), the EMD is a specific algorithm and therefore no selection of transform (and the corresponding bias that selection may introduce) is required.

The second step in the HHT is to apply the Hilbert algorithm to each IMF to create a time-frequency representation. The HHT is superior to the FFT because the frequency resolution is not dependent on the time-window width (see discussion of the uncertainty principle in Wavelet Transform, above). By applying the HHT continuously to the incoming signal and watching the algorithm output for strong variations, the start and end of marine mammal calls can be detected. Once found, the technique segments the IMFs into portions based on deviations in frequencies;

removes ambient noise by amplifying the highest frequencies and attenuating the lowest frequencies; and then reassembles the segments into an acoustic feature ready to be passed to a classifier. The nature of the algorithm allowed Adam (2006, 2008) to separate overlapping signals into individual calls. Detection rate was greater than 90% when tested on overlapping killer whale vocalizations.

3.4.1.2 Adaptive Notch Filter – Johansson and White (2004) used a type of parametric model known as an adaptive notch filter to track the dominant frequencies in an incoming signal. Contrary to most detection methods, the spectrogram of the incoming signal does not need to be calculated as the model is applied directly to the time domain waveform. The model makes a prediction of the next signal sample based on previous samples using the Gauss-Newton type recursive prediction error algorithm (Chen et al., 1992). Model parameters are then adjusted in order to minimize the difference between the model-predicted signal and the actual signal. In regions of the signal where a call is absent, the model parameter estimates fluctuate. Once a call appears, the estimates become stable and can be used as both indicators of detection as well as elements of the feature vector. This technique works well with low SNR signals but has some difficulty with overlapping signals, especially cetacean clicks which tend to 'hijack' the tracking away from tonal signals. While testing was performed on previously-recorded sound files containing right whale calls, the method was quick enough to allow implementation in real-time (Johansson & White, 2004).

3.4.2 Detection/Classification

3.4.2.1 Spectrogram Correlation – Spectrogram correlation is a well-known technique that has been tested on the calls of many different species (bowhead whales: Mellinger & Clark, 2000; right whales: Munger et al., 2005; sei whales, Balaenoptera borealis: Baumgartner & Fratatoni, 2008; Blainville's beaked whales, pilot whales, and Risso's dolphins: Harland, 2008). For this method, reference calls from the species of interest are converted into sparse matrices of reference coefficients, or 'kernels', with one kernel for each call type. These reference kernels are then constantly cross multiplied on a cell-by-cell basis with the incoming spectrogram signal to form a 'classification factor' at each time increment. A positive classification factor indicates some degree of match. The kernels are created by trial-and-error either synthetically or from previously analyzed recordings, in order to optimize the detection results in a training set. Proper selection of reference signals is critical to the performance of the detector and thus this method is only suited to detection of well-known, stereotyped calls. Mellinger and Clark (2000) achieved a 97.5% detection rate when applying spectrogram correlation to the end notes of bowhead whale songs. If the signals of interest are relatively stereotyped, this method can be successfully applied even when only a small number of reference calls are available.

Depending on the number of reference matrices used, this technique can be prohibitively processor-intensive. In order to speed up the calculations, Harland (2008) employed an energy detector as described above to first detect acoustic features of interest.

3.4.2.2 Matched Filter – The matched filter detector is similar to spectrogram cross-correlation, but is performed on the time-series of the signal instead of the spectrogram. A matched-filter ‘kernel’ of the feature to be detected is produced, either synthetically or using a high-quality recording, and is then cross correlated with the incoming signal. Matched filters are extremely efficient at detecting signals in Gaussian ‘white noise’, but the ‘colored noise’ typical in ocean environments poses more of a problem for them. As with spectrogram cross-correlation, the selection of kernel(s) is critical to detector performance. Matched filters are only appropriate for detection of well-known stereotyped acoustic features such as blue whale calls (Stafford et al., 1998; Mellinger et al., 2004a) or fin whale calls (Thompson et al., 1992), and their performance suffers in the presence of even a small amount of variation in the call compared to the kernel. Weisburn et al. (1993) found that a Hidden Markov Model detector performed better than a matched filter for detecting notes in a song of an individual bowhead whale, and Mellinger and Clark (2000) found that both spectrogram correlation and neural networks performed better than a matched filter when applied to bowhead whale calls.

3.4.2.3 Artificial Neural Networks – Mellinger (2004) developed a neural network to detect right whale calls in an incoming signal. The neural network (described in detail in the Classification section, above) was applied to a window of a normalized spectrogram at each time bin, and the resulting detection parameter was compared to a user-determined threshold value to determine whether an event had occurred. The author found that this technique performed better than spectrogram correlation. Mellinger and Clark (2000) determined that neural networks performed better than both spectrogram correlation and matched filters at detecting bowhead whale calls, achieving a 98.4% detection rate. However, neural networks require very large training sets (over 8000 marked calls in Mellinger 2004) and consequently a great deal of operator time for data preparation.

3.4.3 Feature Extraction/Classification

3.4.3.1 Hidden Markov Models – Hidden Markov Model (HMM) theory was developed in the late 1960s by Baum and Eagon (1967), and it is now commonly used for human speech recognition (Rabiner et al., 1983; Levinson, 1985; Rabiner, 1989; Rabiner et al., 1996). To create a HMM, a vector of features is extracted from a signal at discrete time steps. The temporal evolution of these features from one state to the next is modeled by creating a transition matrix, M, where entry M_{ij} is the probability of transition from state i to state j, and an emission matrix, E, where entry E_{is} is the probability of observing signal s in state i (Rickwood & Taylor, 2008). A different HMM is created for each species in the data-set and a call is classified by determining which of the HMMs has the highest likelihood of producing that particular set of signal states. Training HMMs requires significant amounts of computing, and proper estimation of the transition and output probabilities is of crucial importance (Makhoul & Schwartz, 1995). Excellent tutorials on HMMs can be found in Rabiner (1989) and Rabiner and Juang (1986).

A significant advantage inherent to HMMs is their ability to model time and spectral variability simultaneously (Makhoul & Schwartz, 1995). They are able to model time series that have subtle temporal structure and are very efficient for modeling signals with varying lengths by performing non-linear temporal alignment during both the training and classification processes (Clemins et al., 2005; Roch et al., 2007; Trifa et al., 2008). Using HMMs, one can build complex models to deal with complex bioacoustic signals (Rickwood & Taylor, 2008), but care must be taken when choosing training samples to obtain high generalization ability. The performance of an HMM is influenced by the size of the training set, the feature extraction method used, and the number of states in the model (Trifa et al., 2008). Recognition performance is also affected by noise (Trifa et al., 2008).

In addition to being successfully used in human speech recognition, HMMs have been used to classify the vocalizations of humpback whales (Suzuki et al., 2006), dolphin whistles (Sturtivant & Datta, 1997, Datta & Sturtivan, 2002), killer whales (Brown & Smaragdis, 2008, 2009), beluga whales (Clemins & Johnson, 2005; Leblanc et al., 2008), bowhead whales (Weisburn et al., 1993; Mellinger & Clark 2000), wolves (Curless et al., 2007), elephants (Clemins et al., 2005), and birds (Kogan & Margoliash 1998; Trawicki et al., 2005). HMMs have been found to perform as well as, or better than, both GMMs and dynamic time warping (Weisburn et al., 1993; Kogan & Margoliash, 1998), and are becoming more common in marine mammal classification studies.

3.4.3.2 Dynamic time warping -- Dynamic time warping (DTW) is a class of algorithms originally developed for automated human speech recognition (Myers et al., 1980). It is a dynamic programming technique for quantitatively comparing curves of similar shape but different durations using local extension and compression of the time axis of frequency contours (Deecke & Janik 2006, Roch et al., 2007). There are different DTW techniques (for example Itakura, 1975; Sakoe & Chiba, 1978; Kruskal & Sankoff, 1983; Foote, 2000; Chai & Vercoe, 2003), but all are based on comparing a reference call, R(n) to a test call, T(m), where R(n) and T(m) are multidimensional feature vectors describing the sounds. The first step in DTW is to construct a difference matrix, D(n,m), where each element in D(n,m) is equal to the difference in the corresponding elements of the two sounds. To do this, one sound is place on the vertical axis and the other on the horizontal axis and a search is performed to find the optimal path m=w(n) in the (n,m) plane to minimize a total distance function D, where:

$$D = \sum_{n=1}^{N} \widetilde{d}(R(n), T(w(n))),$$

and $\widetilde{d}(R(n), T(w(n)))$ is the local distance between frame *n* of the reference pattern and frame *m=w(n)* of the test pattern (Myers et al., 1980; Brown &, Miller 2007). In order to find this path, several parameters must be specified, including: endpoint constraints on the path, local continuity constraints of the path (for example, directions and slopes that the path can move in), global path constraints (limitations on where the path can lie), axis orientation, and distance measures used to determine the optimal path (For a discussion of how these parameters affect the implementation and performance of DTW algorithms, see Myers (1980)). For classification, distances resulting from pairwise comparisons of sounds are clustered into categories using methods such as k-means cluster analysis, or artificial neural networks (Deecke & Janik, 2006; Brown & Miller, 2007).

Dynamic time warping was first used to classify marine mammal sounds by Buck and Tyack (1993). They classified three signature whistles from each of five bottlenose dolphins, with 100% correct classification. Dynamic time warping has also been used to classify stereotyped pulsed sounds produced by killer whales, both in captivity (Brown et al., 2006) and at sea (Deecke & Janik, 2006; Brown & Miller, 2007). In all of these studies, calls were classified to categories that were perceptually identified by humans with very high correct classification scores. The sounds being classified in both the bottlenose dolphin and the killer whale studies were stereotyped pod- or individual- specific calls. The datasets used contained few contours that were either virtually identical within groups or well separated in frequency. As a result, DTW has been demonstrated to work well for stereotyped sounds, but it may not be appropriate for sounds that cannot be accurately represented by a finite number of templates (such as whistle repertoires of delphinid species). In addition, noise and overlapping signals degrade the performance of DTW algorithms, making them difficult to apply to many field recordings. In fact, because of its failure to model human speech reliably in all but the most ideal situations, DTW has been largely replaced by other techniques such as Hidden Markov Models and artificial neural networks in most recent human speech analysis (Anderson et al., 1996).

3.4.4 Detection/Feature Extraction/Classification

3.4.4.1 Hypothesis Testing – The multiple stage hypothesis testing technique, developed by Urazghildiiev and Clark (2007) and Urazghildiiev et al., (2008), is a statistical method for detecting and recognizing marine mammal signals that can be modeled as polynomial phase signals. It involves a spectrogram-based detector in the first stage, followed by a feature vector testing technique for identification. The detector calculates a test statistic, $z(i)$, based on the output of a 2-dimensional FIR filterbank that is applied to the spectrogram of the input data. The test statistic is then compared with a threshold, C, and a signal is detected if $z(i) \geq C$. The threshold, C, is user-specified and chosen based on the noise conditions in the recordings and the desired correct detection vs. false alarm rate.

The ‘recognizer’ is based on features (signal duration, bandwidth, etc.) obtained from empirical distributions computed using a training data set. The following discriminant function is calculated:

$$h(v) = \sum_{i=1}^{K} h(v_i)\,,$$

$$\text{where } h(v_i) = \begin{cases} 0 \text{ if } v_{i\,min} \le v_i \le v_{i\,max} \\ A_{i\,min}(v_i - v_{i\,min})^2 \text{ if } v_i < v_{i\,min} \\ A_{i\,max}(v_i - v_{i\,max})^2 \text{ if } v_i < v_{i\,max}, \end{cases}$$

and $v_{i\,min}$, $v_{i\,max}$ define the bounds of the i^{th} feature in the feature vector and $A_{i\,min}$ and $A_{i\,max}$ are scalars. A signal is present when $h(v) \le$ the threshold value C_R. Parameter values are optimized through analysis of the training data set.

Urazghildiiev and Clark (2007) used this method to detect the contact calls of North Atlantic right whales and found that it out-performed a detector based on the generalized likelihood ratio test (GLRT, described in Urazghildiiev and Clark (2006)) when FHAT wavelets were used as a kernel in the two-dimensional filter-banks. The filter-bank-based method had fewer false alarms, due to the fact that the FHAT wavelet can suppress wideband noise transients. This is a particular advantage for detectors that will be used in locations subject to broadband noise pulses such as seismic airgun signals. The filter-bank-based detector was more robust to noise in general and provided a significant decrease in run-time as compared to the GLRT-based solutions. Urazghildiiev et al. (2008) tested the filter-bank-based detector on recordings containing right whale upsweeps and fin whale 20 Hz pulses and down-sweeps. The detector detected and recognized 87% of 178 right whale upsweeps with a false alarm rate of 12 false alarms/24 hours of observations. It also detected 76% of 893 fin whale down-sweeps and 77% of 904 20 Hz pulses, with 33.5 false alarms/24 hours of observations. The main contributors to false alarms were the presence of mechanical noise, humpback whale sounds, sei whale sounds, and other transients similar to right whale upsweep and fin whale down-sweep sounds.

This technique can be modified and applied to the automatic detection and recognition of other marine mammal species whose signals can be modeled as polynomial phase signals. Likely candidates are species such as humpback and sei whales.

3.4.4.2 Morphological Processing – Thode et al. (2008a,b; 2009) and Mathias et al. (2008) have developed a four-stage system for the detection and classification of bowhead whale calls using Java based scripts. This system is different than many others because it was created for use in shallow Arctic waters where coherent signal detection techniques cannot be used. This system also includes localization capabilities, but these will not be discussed here. The four stages of this technique are: 1) incoherent “energy” detection; 2) regular interval removal; 3) image processing; and 4) feature extraction, and neural network processing.

The first stage in this system is an energy detector that searches for any transient signal that exceeds a preset SNR for at least one-tenth of a second. The Java routine imports data into memory as short ‘chunks’, and then converts the time series into a power spectral density. The program then computes the sound exposure level (SEL, dB re 1uPa^2-s) over 37 Hz chunks of bandwidth, with the bandwidths overlapping 50%. These incoming data chunks are incorporated into a running average of the “mean” background noise level. Once the running average is established, each new SEL estimate in a given frequency band is compared with the running average for that same band. If the ratio of the incoming to mean SEL values exceeds a threshold of 6 dB (a factor of 2) over any band, then the potential transient signal is flagged. Once subsequent values of the SEL fall below the threshold, an event is logged to file. Computing multiple narrowband incoherent detectors, vs. one broadband detector, increases the likelihood of detecting a narrowband frequency-modulated signal over broadband impulsive signals.

The second stage of the Java script removes sounds that occur at regular intervals, such as airgun signals. This stage is doubly useful because it amounts to automatic detection of airgun pulses whose acoustic parameters can then be computed and logged without operator intervention. The stage works by looking 40 seconds into the future and past, relative to a current detection of interest. If other detections exist within the 80 second window that share the same peak frequency and duration as the detection in question, then these detections provide a set of candidate time intervals to test. For each candidate time interval, the program then jumps four intervals into the future, and four into the past, and checks whether detections with similar peak frequencies and durations exist at those predicted interval times. If at least six out of these eight trial interval times contain detections that match the peak frequency and duration of the current detection, then the current detection is flagged as being "regular" and is rejected. This stage was able to remove between 30 and 50% of the 5,000 to 9,000 airgun pulses that were present in a day's worth of Thode et al.'s (2008a, 2009) data.

In the third stage, image processing, the time series of the data is converted into a spectrogram image. The grayscale image is then converted into a binary image which contains a series of "segments" that contain the time-frequency contours of potential whale calls. Because calls often vary in intensity throughout the call, a whale call is often broken into a set of disconnected segments during the binary conversion. A morphological "opening" and "closing" operation is thus performed on the image to first remove small objects, and then link surviving objects that lie within 0.15 seconds and 10 Hz of each other (Gonzalez & Woods, 2002; Asitha et al., 2008). A subsequent operation identifies harmonics in calls, and thus links disconnected segments into a single call. Frequency and duration values are extracted from the connected components in the binary image using segmentation techniques (Haralick, 1993) and stored to file, along with a compressed version of the binary image for future use.

The fourth stage, neural network filtering, collects 25 normalized feature values from every candidate output of stage three, and passes this feature vector into a multilayer feed-forward neural network. Training was conducted using manually-reviewed data from six non-consecutive days, producing 141,000 manually-flagged examples of whale calls, and 1.15 million detections that were deemed "false alarms", as they had not been flagged by manual analysts—thus a ratio of eight false alarms for every true call going into the network. Once training had been completed, it was found that if a candidate signal whose feature vector generated a network output of less than -0.8 was rejected, the number of false alarms to true calls fell to 1.5, at the cost of sacrificing about 10% of the true calls. Further reductions in the false alarm rate are expected to be achieved in the localization stages, but specific results were not available by the deadline of this report.

Mathias (2008) has conducted work on distinguishing upsweeps, downsweeps, and more complex modulated calls, using both linear discriminant functions and neural networks. The challenge of the task has been increased due to lack of consensus between human analysts over the precise definition of some of the classification categories.

3.5 Detection and Classification Software

There are several software packages available that can be used to analyze data collected using fixed PAM technologies. These range from freely available (free and share-ware), open-source software (e.g., *XBAT* and *PAMGUARD),* to relatively expensive commercially distributed packages (e.g., *Signal* and *Songscope*). Some are fully automated, while others require varying degrees of user interaction or expertise. The detection and classification capabilities vary greatly from program to program, with some able to perform both detection and classification and others with the capability to accomplish only one or the other. Most of these software packages are capable of handling a range of sampling frequencies, from hundreds of Hz to hundreds of kHz. The availability, cost, user-friendliness, and detection/classification capabilities of available software packages are reviewed in Table 2.

Most of the software programs in Table 2 (with the exception of *ROCCA*, *Leafy Seadragon*, and *Triton*) have automated detection capabilities. Probably the most commonly used detection technique is spectrogram cross-correlation (see Section 3.4.2.1). Because this technique is based on using one signal to detect other similar signals, spectrogram correlation is well suited for stereotyped signals such as fin or blue whale calls. However, it generally does not work well for more variable signals such as dolphin whistles, burst pulses, and the more variable sounds of some species of baleen whales and pinnipeds (for example, humpback whale, bowhead whale, grey whale, bearded seal and harbor seal sounds). To detect these more variable signals, a more general technique such as band-limited threshold detection is necessary (see Section 3.1.1). In this method, a signal is detected when the energy or amplitude of the incoming signal exceeds a user-defined threshold within a user-defined frequency bandwidth (Brandes, 2008: Ward et al., 2008). However, because whistle contours typically cover a large bandwidth and are relatively low in amplitude, energy detection methods do not always perform well for these types of signals. Energy detection does work well for high intensity, impulsive signals such as sperm whale clicks and odontocete echolocation signals (Kandia & Stylianou, 2006; Tieman et al., 2006; Roch et al., 2008; Tieman, 2008; Ward et al., 2008).

Because spectrogram correlation is based on detecting a specific type of signal, it is, by definition, an effective method for classification of stereotyped signals. As a result, methods for the detection and classification of stereotyped signals are relatively well developed. A major gap in auto-detection capabilities lies in the ability to reliably detect and classify the calls of species that produce variable signals such as dolphins, some baleen whales, and pinnipeds. Only a few of the software packages listed in Table 2 have the capability to classify whistles (*PAMGuard*, *Rocca*, *Avisoft SASLab Pro*, *Leafy Seadragon*, *Songscope*, and *MMADAS*), and only *Avisoft SASLab Pro* and *Songscope* have the potential to classify baleen whales that do not produce stereotyped signals. Both of these software packages automatically measure parameters from detected signals and create classification algorithms (Discriminant Function Analysis in *SASLab* and Hidden Markov Models in *Songscope*) based on these measurements. Correct classification rates for all of these tools are generally below the standard of near certainty that is applied to visual species identification. From the perspective of studying behavior and abundance, the most critical area for future development in the detection and classification of marine mammal signals lies in the advancement of methods for the classification of variable signals.

Hand-in-hand with this need is the capability to extract frequency contours. Most classification algorithms are based on features extracted from frequency contours and automating this process is crucial to the efficient analysis of fixed PAM data. Much work has recently been undertaken in this area of research, but a reliable method for automatically extracting frequency contours has yet to be developed and implemented into software. *Avisoft SASLab Pro* has contour extraction capabilities, but this software package is relatively expensive, which may make it prohibitive for use by many researchers and managers. *Songscope* also has contour extraction capabilities and is a more affordable alternative. *PAMGuard* has some capabilities that allow automatic extraction of whistle contours, but this algorithm is generally only able to extract small fragments of whistles, or single whistles are often extracted as multiple whistles, especially if there is a lot of amplitude modulation within the whistle (Yack et al., in press). *Rocca* also has the capability to extract whistle contours, but significant user interaction is necessary, making it somewhat inefficient for real-time use in the field. Under JIP contract, work is underway to more fully automate this process in *Rocca* and to improve *Rocca's* classification abilities. This new version of *Rocca* is being developed as a *PAMGuard* module and will be available as open-source software on the *PAMGuard* website (www.*PAMGuard*.org).

Based on the capabilities of available software, the most critical gaps in our ability to efficiently analyze data collected using fixed PAM technologies lie in the detection, feature extraction and classification of variable signals.

4 Discussion

4.1 Call Detection Summary

Methods for the detection of stereotyped calls such as those from some baleen whales (e.g., fin or blue whale calls) are relatively well developed and commonly used (Table 2). Spectrogram correlation and matched filters are the most popular methods for detecting stereotyped calls and work well under good SNR conditions. Neural networks produce high detection rates when applied to stereotyped calls; however they can require a very large training data set. Detection methods for impulsive sounds such as clicks are also relatively well developed and effective for many marine mammal sounds. Energy threshold detection is simple, effective, and computationally inexpensive. This method has been shown to successfully detect clicks from many species. However, these methods can lead to high false detection rates in the presence of O&G E&P such as airgun impulses, noise from production machinery, and ship noise.

Future research into detection methods should focus on detection of variable, low SNR calls such as delphinid whistles and non-stereotyped baleen whale calls. The wavelet transform methods show much promise and are quite robust at detecting killer whale calls. The overcomplete wavelet transform performed very well with bottlenose dolphin whistles. These methods should be investigated further and applied to different species and in different environments, with a variety of ambient noise characteristics. This should include tests of how they would perform in the presence of interfering signals such as seismic exploration pulses, oil and gas industry platform and drilling noise, vessel traffic, sonar and other man-made sources.

4.1.1 Feature Extraction

Feature extraction is a crucial step in the detection/classification process and yet, it seems to be among the least rigorously tested and published of all the steps. The features that are entered into classification algorithms as well as the accuracy with which these features are measured can have significant impacts on the accuracy of the classifier. In addition, traditional, manual methods of feature extraction are time consuming and subjective. Not only should effort be put into further evaluating the automated methods discussed here and experimenting with additional methods, but making these methods available for use by many should be a high priority. Most authors discuss extraction methods only briefly and then move on to the more central focus of their research. Peak tracing and warping-based signal decomposition both seem to be promising methods, especially for the extraction of variable, overlapping calls and further work should be done to evaluate and improve upon these and similar methods.

4.1.2 Classification

Classification of marine mammal sounds is a rapidly expanding field of research. Classification of variable signals such as delphinid whistles and clicks is one of the most challenging problems faced. Of the many classification algorithms available, several seem especially promising for furthering this area of research and providing reliable methods for classifying sounds from some of the more 'challenging' species. Tree based classification is one of the most commonly used techniques and is one of the only techniques that has been tested on data-sets with large numbers of species. As a result, correct classification scores are not as high as those reported for other methods that were tested on small subsets of species. Results of tree-based studies do show potential, however, and the fact that tree-based classifiers are non-parametric, intuitive and transparent and accommodate for diversity within species makes these classifiers worth further testing and development.

Gaussian mixture models and hidden Markov models are two more techniques that show promise. Both are well suited for modeling complex bioacoustic signals and have been used to successfully classify the calls of many different species, both marine and terrestrial. Caution does need to be used however, as the choice of initial parameters is of crucial importance and training requires large amounts of data.

Artificial neural networks, although considered a 'black box' and questionable by some, are well suited for problems involving arbitrary distributions and noisy input. They have produced good results, outperforming methods such as spectrogram correlators. However, ANNs have not been tested using a dataset that includes a large number of species, which would be a valuable undertaking.

In addition to applying promising methods to data-sets that include a large number of species, it would be beneficial to experiment with using different types of feature vectors as input to classification algorithms. Commonly used features include variables measured from spectrograms, but these do not provide a complete representation of the call and differences among species may therefore be missed. More complete time-frequency information can be captured by using entire frequency contours or spectrograms as feature vectors. Feature vectors that are not based on spectrograms have also shown promise. Transforms such as wavelet transforms and cepstral features may provide greater separation among species than do spectrogram-based methods. These and other feature vectors should be explored in order to find the best combination of features and classification algorithms for the classification of species of interest. Different combinations may be optimal for different species-sets, as distinguishing features are likely not the same for every species. Because of this, it may also be possible to increase correct classification rates by basing decisions on the output of more than one classification algorithm.

4.2 Recommendations and Ways Forward

4.2.1 Methodological Considerations

When developing methods for the detection and classification of marine mammal sounds, it is important to take into account the fact that these sounds can have great variability in frequency range, source level, and propagation characteristics, both between, and within species and, for some species, individuals. This variability is often related to taxonomic, geographic, and even cultural differences in sound types produced. Therefore, systems used for automatic detection and classification in different regions will need to be configured differently to account for these different characteristics. For example, baleen whale calls are much lower frequency and therefore travel much greater distances than delphinid whistles and clicks. In addition, the long-distance calls produced by many baleen whales are stereotyped and are thus suitable for detection/classification using 'template' matching methods. These methods are not suitable for the more variable calls typically produced by dolphins and some types of baleen whales and pinnipeds (see Sections 5.2.1 Spectrogram Correlation and 5.2.2 Matched filter. When designing a system to detect a large number of species, several different methods may need to be incorporated, depending on the species of interest.

It is also important to understand the vocal behavior of the species of interest. Some marine mammals only vocalize at certain times of the year or during certain behavior states or events. This can vary with sex, age class behavioral context or a variety of other factors. Assessing the affects of these factors on vocal behavior and the types of sounds produced by marine mammals is a complicated and difficult endeavor. Failure to detect acoustic signals from marine mammals does not always mean that they are not present. In order to fully assess the performance of a detector, it is necessary to gain an understanding of where and when different species are most likely to be acoustically active. Natural variation in vocal behavior is a subject about which very little is known for the majority of marine mammal species.

Additional factors to bear in mind when considering automated detection and classification methods include the effects of underwater sound propagation and noise. Some fixed installation PAM systems are seafloor-mounted and this potentially places them in a region away from vocalizing animals or in a region where propagation can be impaired by bathymetry and other underwater features (e.g. reef formations). Most species of dolphins and sirenians, many species of baleen whales and some species of pinnipeds live primarily near the surface of the water. As such, signals that are produced are affected by a variety of factors before they reach a seafloor receiver. For example, surface attenuation effects and thermal stratification such as surface ducts can result in propagation effects that can significantly reduce (or enhance) the amount of energy reaching hydrophones located on the seafloor. In addition, signals of interest can be obscured or masked by overlapping vocalizations produced by other individuals or species, or anthropogenic noise such as that produced by vessels, seismic exploration, and sonars. Finally, self-generated noise produced by mobile components within the recorders themselves can also negatively impact the ability to detect and classify signals. To summarize, propagation effects, ambient noise, and interfering signals can reduce SNR and make it difficult to detect and extract salient features.

Another important consideration when assessing automated detection and classification of marine mammal sounds is the trade-off between missed calls and false detections (or incorrect classifications). In situations involving rarely occurring species, species that vocalize infrequently, or species of great concern, it is advantageous to set the detector or classifier to a relatively high sensitivity (i.e. low threshold for detection) so that relatively few calls are missed or incorrectly identified but a large number of false detections occur. In this case, detections can be validated manually to determine which were produced by the species of interest (Mellinger et al., 2004b, Munger et al., 2005, Mellinger et al., 2007b). For commonly occurring species, or species that vocalize frequently, the detector or classifier can be relatively insensitive so that there are few incorrect and a high proportion of correct detections or identifications.

The types of datasets collected using fixed installation PAM systems are typically very large. The actual size (in bytes) will depend on sample rate, duty cycle, and length of recorder deployment or recording period. To accommodate such voluminous data sets, efforts should focus on developing automated detection and classification algorithms that are as efficient as possible and that store detections using data compression, reduction or organization techniques that require only a small fraction of the storage space of the original recording. For example marine mammal calls can detected can be saved using some important features (e.g. time start and end, frequency start and end) of the original signals, so that the entire signal does not need to be saved. However, it is also important to be able to restore or reconstruct the original signal if more detailed analysis or validation is needed at some point in the future.

4.2.2 Data-Set Considerations

The development and validation of methods for the detection and classification of marine mammal acoustic signals, especially methods that are applicable to a large variety of species, require voluminous amounts of data. It is necessary to obtain both a training data-set and a testing data-set that are large enough to capture as much of the variability of the vocal repertoire of the species of interest as possible. The amount of data necessary increases rapidly with the amount of variability in the vocal repertoire or with the number of species to be included in the algorithms. In order to capture as much of the vocal repertoire as possible, data should be collected from animals in different behavior states, locations, group sizes, times and seasons. For some species, geographic variation may be so great that it is necessary to develop entirely different algorithms for the same species in different locations (i.e. different stocks or populations). It is also necessary to obtain recordings of different quality (e.g., a wide range of SNR) to capture the variability of the non-target sounds such as ocean ambient, non-target species, and anthropogenic noise. Detector and classifier performance often change substantially with the same target sounds when they appear against different background noise. For example, a detector designed using only high SNR data may perform poorly when SNR is low. In addition, interfering noises such as seismic pulses or overlapping vocalizations may restrict the accuracy of feature extraction or classification algorithms. Finally, recordings used for species identification must be ground-truthed in order to verify that calls used for training classification algorithms are indeed produced by the species of interest. In order to do this, acoustic recordings need to be paired with visual observations or other monitoring methods/technologies. In addition, the sounds being recorded should be localized to be sure that they are being produced by the animals being observed visually and not by some other group in the area.

The collection of field recordings and visual observations is time consuming and expensive, and therefore, it is difficult for most researchers to obtain the large data-sets that are optimal for developing detection and classification algorithms. Databases of ground-truthed marine mammal recordings that can be accessed and used by many different researchers would allow algorithm development to take place much more efficiently and accurately. The Macaulay Library of animal recordings (www.animalbehaviorarchive.org), maintained by the Cornell Laboratory of Ornithology is an excellent example of such a database, although it is designed as a sound library, and the recordings are not all necessarily appropriate for the uses described here. Because this library functions as a 'museum' of sounds, it contains mostly high-quality, high-SNR recordings which may not capture the full range of variability in target and non-target sounds. Another site, 'MobySound' (www.mobysound.org) provides a database that has been specifically designed for use in research and development of automatic call recognition. The recordings are annotated, long and continuous, and of variable SNR. All of these qualities are important for this type of research. There are currently eight baleen whale and four odontocete species included in the MobySound database. With a larger number of species, this website will be a valuable resource for researchers developing detection and classification algorithms.

Another valuable resource for researchers when developing detection and classification methods is the ability to compare different methods on the same datasets. This provides an objective way to compare and evaluate different methods and possibly identify combinations of methods that might be appropriate for specific situations. This opportunity has been provided several times at the International Workshops on the Detection, Classification, and Localization of Marine Mammals Using Passive Acoustics in Nova Scotia (Desharnais & Hay, 2004), Monaco (Adam, 2006b), and Boston (Moretti et al., 2008). Each of these workshops focused on different target species (north Atlantic right whales, sperm whales, and beaked whales, respectively). They allowed researchers to test their algorithms on a common dataset and then come together to discuss the strengths and weaknesses of the different methods. Future workshops in this series will be focused on the analysis of real-world complex acoustic scenes and the use of context for identifying acoustic components of interest. Additional workshops such as these would be valuable for the advancement of technology in the areas of detection and classification.

4.2.3 Classifier Considerations

Most of the algorithms and software programs discussed in this review are focused on the identification of a single or small group of species. For many applications, however, it is necessary to have the capability to correctly identify any species of the many that might be encountered in an area. Only DFA and classification tree analysis have been tested on a large number of species and few of the available software packages (e.g. *ROCCA*, *Songscope* and eventually *PAMGuard*, via JIP funding) provide multi-species recognition beyond two or three species. One of the challenges in creating multi-species signal classification algorithms is the amount of data necessary for development, testing, and validation. Databases and workshops such as those described above will also make it possible for researchers to develop algorithms that include a larger number of species. In addition, the availability of open-source classification algorithms would allow researchers to compare the performance of classifiers on different data-sets. One such resource is the Weka Machine Learning Project (www.cs.waikato.ac.nz) out of the University of Waikato in New Zealand. This project provides a software package of machine learning algorithms, written in Java that is freely available for researchers to apply to their datasets.

In addition to comparing classifiers, greater consideration should be given to the features that are fed into such classifiers. This is a topic that is not often discussed in the literature and is of crucial importance in the success of the classification algorithm. Effort should focus on exploring different types of feature vectors, including spectrographic measurements, wavelet transforms, cepstral features, and other more complex features of marine mammal sounds. Comparisons should be made to evaluate how different feature vectors perform when applied to the same data-set using the same classification algorithm. The features used to represent a sound are likely to have a significant effect on whether or not the sound can be differentiated from sounds produced by other species.

4.2.4 Remote operation considerations

The ability to run detection and classification algorithms in real-time onboard fixed PAM devices and installations allow onboard processing of data which would, in turn, significantly reduce post-processing time and data storage requirements. The difficulties in accomplishing this depend on the complexity of the signals to be detected, the number of species to be differentiated, ambient noise, and the acceptable numbers of false positive and missed signals. Embedded software will work best in situations where the species to be detected have simple calls with low variability, the number of species to be differentiated is small, and there is limited interfering ambient noise.

Most algorithms that are best suited for real-time remote or autonomous operation are relatively simple detectors searching for stereotyped signals such as fin whale downsweeps, beaked whale clicks, or minke whale boings. Threshold detectors, spectrogram correlators (depending on the number of reference matrices to be used) and the PCA detector are all well suited to real-time applications as they can be set up to run with little or no user-input and operate at real-time or greater than real-time speeds. As described in Section 3.4.2, some detectors can also act as classifiers; however this is generally true only when the signals of interest are relatively stereotyped. When dealing with more complex or variable signals or a large number of species, it may be more effective to run a detector on board the fixed PAM device and then perform the classification step later during post-processing. The detector can either save sound files that contain potential signals of interest or send them to land via satellite, cellular networks, or a cable connection. These files can be further analyzed using software that is more sophisticated and requires more user-interaction such as *ROCCA* or *Songscope*. Although not fully automated, such a two step process will significantly reduce the volume of data that the user needs to analyze and can allow detections to be classified in near real-time.

There are several software packages that are capable of running in real-time and would be good candidates for remote use. For example; *Ishmael, Raven* and *XBAT* all perform spectrogram correlation and can therefore be used to detect and classify signals that contain little variability. *PAMGuard* includes several detectors developed for *Ishmael* as well as a whistle detector and classifier. Other software packages that have the potential for real-time use in remote packages include: *Rainbow Click, Avisoft SASLab Pro, Syrinx, ACDC, MMDAS,* and *SPUD* (see Table 2 for more details).

4.2.5 Oil and Gas Exploration and Production Considerations

The ability to automatically detect and classify sounds produced by marine mammals can be compromised by noise produced during oil and gas exploration and production (OG EP) activities. Noise produced by factors such as vessels, drilling and construction can mask marine mammal sounds, causing automated detectors to miss them. Even if marine mammal sounds are detected in reduced SNR conditions caused by OG EP activities, it can be difficult to automatically extract features from them. For example, drilling sounds contain low frequency, tonal components that may overlap with sounds produced by some marine mammal species such as bowhead whales. At the point of overlap between the whale vocalization and the drilling noise, automated feature extractors may extract features from the tonal noise rather than the marine mammal sound. This will lead to incorrect feature vectors which will then confound the classification results.

Another example of an OG EP activity that will affect automated detection and classification systems is seismic exploration. Airgun signals (short pulses at regular intervals) may cause false detections, as much of their energy lies in the same frequency band of many marine mammal vocalizations, especially clicks produced by many species of odontocetes. The work of Thode et al., (2008a, b; 2009) and Mathias et al., (2008) (see Section 6.4.2) are examples of detectors that were specifically developed to recognize airgun pulses and remove them before they are counted as potential detections of interest. Automated detection and classification systems that will be used during seismic surveys should be configured so that they can recognize and appropriately account for airgun pulses.

When evaluating automatic tools for detection, feature extraction, and classification, during OG EP activities, it is important to evaluate them in all noise conditions that may be encountered in the field. It is also important to bear in mind the goals of the acoustic monitoring and evaluate what information is important. For example, it may be sufficient to simply detect the presence of a 'marine mammal'. In this case, a detection need only be identified as 'marine mammal' or 'non-marine mammal'. In other cases, it may be important to distinguish between whales and dolphins. In still other cases, where protected or sensitive species are involved, it may be necessary to identify sounds to species (e.g., blue whale, false killer whale, etc). The level of identification needed will directly impact the classification algorithm that should be used. In addition to the level of classification, the false alarm rate and rate of missed sounds that is allowable will most likely differ from application to application. In some cases, for example, when evaluating the effect of an activity on the vocal behavior of marine mammals, it may be important to detect all or most marine mammal sounds that occur. In other cases, (e.g., such as during mitigation exercises) it is only necessary to note the presence or absence of marine mammals during a particular time period, and thus not every vocalization needs to be detected. The information that is necessary for each scenario will govern not only the choice of detector, but also the threshold settings within that detector.

In summary, it is not possible to recommend one system for all situations. The user must evaluate the noise conditions and information required and choose an automated detector, feature extractor and classifier accordingly.

4.3 Conclusions

As the use of fixed PAM to monitor marine mammals becomes more widespread, and as longer deployments and recordings result in greater quantities of data, automated methods for the detection and classification of marine mammal vocalizations will become more essential. Several software packages are available for detection or classification, but few perform both tasks effectively, and none are able to accurately classify the vocalizations of a large number of species.

Several methods possess good potential for the detection and classification of marine mammal calls, especially more stereotyped calls such as those produced by baleen whales and beaked whales. In order to be used successfully as mitigation and monitoring tools, detection/classification algorithms must be able to detect and identify all sounds that may be encountered in an area and not just some subset such as those with simple structures or that are stereotyped. Therefore, promising software should be tested on a larger number of species and signals, especially on species with highly variable sounds (such as those produced by dolphins, some baleen whales, and pinnipeds). The ability to automatically determine when species of interest are vocalizing will allow more and larger areas to be monitored for seasonal occurrence, relative abundance, distribution, migration routes and other basic aspects of the biology of marine mammals. Attributing the function of detected sounds to aspects of the animals biology, such as courtship and breeding activity, foraging, and social communication (e.g., alarm calls) will provide important information about the effects of noise on biology of these animals. This, in turn, will allow for critical habitats and behaviors to be identified so that more effective monitoring and mitigation plans can be developed. Together with PAM techniques, automatic detection and classification methods will provide a way forward for responsible management of living marine resources in areas where oil and gas exploration and production are planned or occurring.

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5 Tables

Table 1. Species classified, variables measured, and correct classification scores for marine mammal classification studies using multivariate discriminant function analysis.

Species classified	Variables measured	Correct classification score	Reference
Bottlenose dolphin, Atlantic white-sided dolphin, Atlantic spotted dolphin, spinner dolphin, pilot whale	Beginning, ending, minimum, and maximum frequencies, duration, number of inflection points	70%	Steiner, 1981
31 odontocete species, 9 mysticete species, 14 pinniped species, manatees	91 statistical measures	50%	Fristrup & Watkins, 1993
Amazon river dolphins, bottlenose dolphins, dusky dolphins, spinner dolphins, Atlantic spotted dolphins, Pantropical spotted dolphins, tucuxi	Beginning, ending, minimum and maximum frequencies, duration, number of inflection points, slope of the beginning and ending sweeps, presence of harmonics, break in contour	65%	Wang et al., 1995
Nine odontocete species and one mysticete species		28%	Matthews et al., 1999;
False killer whale, short-finned pilot whale, long-finned pilot whale, white-beaked dolphin, Risso's dolphin	Beginning, ending, minimum, and maximum frequencies, duration, number of inflection points	55%	Rendell et al., 1999
Spinner dolphins, spotted dolphins, striped dolphins, short-beaked common dolphins, long-beaked common dolphins, bottlenose dolphins, rough-toothed dolphins, pilot whales, false killer whales	Beginning, ending, minimum, and maximum frequencies, duration, slope of the beginning and ending sweeps, number of inflection points and steps, presence of harmonics, offscale variables, frequency range	41%	Oswald et al., 2003
Right whales	Beginning frequency, sweep frequency, duration, maximum instantaneous bandwidth	60%	Gillespie, 2004
Short-beaked common dolphins, spotted dolphins, striped dolphins, spinner dolphins	Beginning, ending, minimum and maximum frequencies, duration, number of inflection points and steps, presence of harmonics	30-37%, depending on analysis bandwidth	Oswald et al., 2004
Bottlenose dolphins, spotted dolphins, spinner dolphins, striped dolphins, rough-toothed dolphins, *Delphinus* species, false killer whales, pilot whales	Beginning, ending, minimum and maximum frequencies, duration, slope of the beginning and ending sweeps, number of inflection points and steps, presence of harmonics	33% DFA alone, 44% in combination with classification tree analysis	Oswald et al., 2007
Blainville's beaked whales, pilot whales, Risso's dolphins	Relative energy measured from bins 1.5 kHz wide for a total of 32 parameters/click	"Good separation among the three species although with slight overlap between beaked and pilot whales"	Gillespie & Caillat, 2008

Table 2. Software available for the detection, extraction, and classification of marine mammal calls. NA denotes cells for which information was not available.

Product name	Developer	Availability	Cost	Audio formats supported	User-friendliness	Batch processing?	Detection capabilities	Classification Capabilities	Real-time vs post processing	Drawbacks	Other	References snd species
Ishmael	Dave Mellinger, Oregon State University	http://www.pmel.noaa.gov/vents/acoustics/whales/ishmael/download.html	Free	.wav, .aif, .au	Pull-down menus, dialogue boxes, detailed users guide, easy to learn	Yes	Three automatic detection functions: 1) Energy summation, 2) Matched filtering, 3) Spectrogram cross-correlation	none	Real-time and post-processing, supports both operator interaction and automated detection	No classification, not well suited for sound exploration, PC only	Supports multi-channel recording, also has localization capabilities	Detection of alarm calls produced by fowl (Wilson and Evans 2008), Right whale calls (Mellinger et al., 2004b, Munger et al., 2005), sperm whale clicks (Thode et al., 2007), blue whales (Oleson et al., 2007, Stafford et al., 2004)
PAMGuard	Doug Gillespie, Sea Mammal Research Unit, University of St. Andrews, Herriot Watt University, Oregon State University, Scripps Institution of Oceanography	www.pamguard.org	Free, open source	.wav, .aif	Good tutorial and users guide. Users forum Installation/user manuals available via website	Yes	*Click detector*: audio even is defined when signal level exceeds user-defined threshold. *Whistle detector*: areas of spectrogram that exceed background noise level by a threshold value are identified as 'peaks'. When enough subsequent peaks are found, the set of peaks is considered to be a whistle Three automatic *Ishmael* detection functions: 1) Energy summation, 2) Matched filtering, 3) Spectrogram cross-correlation Likelihood detector??	*Click classification*: click events compared to predefined templates. Templates contain four criteria to match against: energy band comparison, peak frequency comparison, mean frequency, click length. *Whistle classification*: based on measurements taken from whistle fragments. Additional classification capabilities under development, such as the *ROCCA* delphinid classifiers	Real-time and post-processing	Whistle detector only detects fragments of whistles	Includes localization, map, radar plug-ins.	Gillespie et al., 2009, Beaked whales (Gillespie et al., 2008), bowhead whales (Thode et al., 2008a,b), dolphins, porpoises and beaked whales (Yack et al., 2009)
Rainbow Click	International Fund for Animal Welfare (IFAW)	http://www.ifaw.org/ifaw_european_union/join_campaigns/protecting_whales_around_the_world/come_aboard_the_song_of_the_whale/download_cetacean_research_software/index.php	Free	.wav	Incomplete help file, many functions not discussed, no users guide, fairly straightforward to use, users newsgroup at: http://groups.yahoo.com/group/ifawsoft/	No	Automatic detection of clicks. First level trigger: incoming wav file is rectified and passed through a low-pass filter. Detection occurs when signal amplitude is above a user-defined threshold. Second level trigger: detection from first level trigger is filtered by user-defined bandpass filter; if energy within a specific bandwidth exceeds a threshold, the detection is accepted as a click	Energy band information can be saved for a specific click, and future clicks can be compared for identification purposes	Real-time and post-processing	Poor help file, no user support, has difficulty with low SNR signals such as sperm whale creaks	Written to run under Windows 2000 and Windows XP operating systems, also has localization capabilities	Sperm whales (Lewis et al., 2007, Jaquet 2006, Kandia and Stylianou 2006, Drouot et al., 2004, Rendell and Whitehead 2004, Gillespie 1997), beaked whales (Gillespie 2008, Gillespie and Caillat 2008)
Raven	Cornell Laboratory of Ornithology	www.birds.cornell.edu/raven	$800 commercial. $400 academic, gov., or non-profit, $100 student; *Raven-Lite* (limited capabilities) - free	.aiff, .wav, .mp3, .aifc, any sound format supported by Apple QuickTime, audio CDs	Contextual menus, full set of toolbar buttons, dialogue boxes, very clear and detailed users manual (Charif et al., 2008), easy to learn and use	Yes	Multiple detectors: 1) band limited energy detector (Mills, 2000) 2) amplitude detector	Spectrogram or waveform correlation. Only works well for stereotyped signals.	Suitable for both real-time and post-processing		Supports detectors written in Java or Python, so developers can write their own (see http://*Raven*SoundSoftware.com)	Not commonly used for detection. One example: detection of alarm calls produced by fowl (Wilson and Evans 2008). Commonly used for signal display and measurement: tucuxi dolphins (Azevedo and Van Sluys 2005), boto dolphins (May-Collado and Wartzok 2007), killer whales (Weiss et al., 2006), humpback whales (Dunlop et al., 2007), bearded seals (Risch et al., 2007), gray whales (Stafford et al., 2007)
XBAT	Cornell Laboratory of Ornithology	www.xbat*XBAT*.org	Free	.aiff, .wav, .au, .w64, .flac, .ogg., .mp3	Not well documented, steep learning curve (but relatively straightforward once learned), users forum: http://groups.google.com/group/xbat-users	Yes	Band-limited energy detector, Spectrogram cross-correlation	Data template detector can be used as a type of classifier. Can run multiple templates simultaneously and tag events according to which template they matched.	Real-time and post-processing	Can be a bit challenging to learn	Supports user-development of new functions (see http://groups.google.com/group/*XBAT*-devel)	Right whales (Parks et al., 2007), bearded seals (Risch et al., 2007, Van Parijs and Clark 2006)
Avisoft SASLab Pro	Avisoft	www.avisoft.com	SAS-Lab light - Free, SAS-Lab Pro - EUR 1500/2200 (educational license/ regular license)	.wav, .aif, .au, .snd, binary	Detailed users manual, extensive list of user-modifiable parameters	Yes	*Pulse detection*: amplitude detector. *Other:* spectrogram cross-correlation	Automatically measures sound parameters from detected events and performs discriminant function analysis to classify	Real-time and post-processing	Expensive	Extracts fundamental frequency contours based on a harmonic peak search on the spectra of the spectrogram	Bottlenose dolphins (Morisaka et al., 2005a, b), killer whales (Shulezhko and Burkanov 2008)
Sound Ruler	Marcos Gridi-Papp, Phys. Science, UCLA	http://soundruler.sourceforge.net/main	Free, open source	.wav	No users manual, some help available on website	No	Uses amplitude/duration thresholds to detect events	None	Post-processing of simple, repetitive signals	Difficulty with complex signals such as whistles	Can automatically measure 35 parameters from an event and export to clipboard or spreadsheet	Bee (2004), Gridi-Papp (2004), birds (Vilches et al., 2006), spiders (Quirici and Costa 2007), frogs (Verdade et al., 2008)
ROCCA (Real-time Odontocete Call Classification Algorithm)	Julie Oswald, Hawaii Institue of Marine Biology	from the author	With collaboration agreement	.wav	Very short users manual, no pull down menus, takes some training to use	No	None	Classifies the whistles of 9 delphinid species based on 12 variables measured from fundamental frequency contour	Real-time and post-processing	Not completely automated. A fair amount of user-input is required.	Working towards incorporation in *PAMGUARD* - estimated to be complete in 2010. Work is currently underway to improve classification success and add species including additional odontocetes and mysticetes.	Oswald et al., (2003, 2007)
Leafy Seadragon	Serge Masse	http://sourceforge.net/projects/c2h/	Free, open source	Only accepts real-time data	Limited online user guide	No	None	Recognizes whistles by comparing them to whistles in a user-created data base	Real-time only	Demanding in processor time. Large database of whistles is required, maximum effective whistle frequency: 11kHz		
Songscope	Wildlife Acoustics	www.wildlifeacoustics.com/downloads/#songscope	$499.95	.wav, .pcm, .aif, .wac, .ssn	Extensive users guide, users group forum (http://pelican.wildlifeacoustics.com/phpBB3/)	Yes	Band-limited energy detector	Creates Hidden Markov Models based on spectral features similar to Mel Frequency Cepstral Coefficients automatically measured from user defined training data	Post-processing	Sensitive to overlapping signals	Also has beamforming capabilities to maximize a selected signals amplitude	birds (Agranat 2007, 2009, Meier et al., 2008)
MMADAS (Marine Mammal Automated Detection System	Kaon Ltd., jointly with QuinetiQ	NA	NA	.wav	NA	NA	Click detector uses both time and frequency domains. Whistle detector uses speech and image processing techniques	Classifies sounds as odontocete whistles, odontocete clicks, sperm whale clicks, low frequency mysticetes, or high frequency mysticetes	suitable for both real-time and post-processing		Also has beamforming capabilities and frequency contour extraction capabilities	
SPUD algorithm (Simple Porpoise Underwater Detector)	Edward J. Harland	NA	NA	.wav	Implemented in *MATLAB*	NA	Multi-dimensional spectrogram correlation to classify individual pulses	Classifies harbor porpoise clicks based on information extracted from click trains	Real-time. Intended for use in small, standalone dataloggers		Also has capability to estimate number of animals echolocating	Harland, 2007; Leeney and Tregenza, 2006
TRUD algorithm (Transient Research Underwater Detector)	Edward J. Harland	NA	NA	.wav	implemented in *MATLAB*	NA	Band-limited energy detector	Spectrogram correlation searches spectrogram for echolocation clicks using a sparse reference matrix (one matrix for each species). Classification based on multiple clicks and inter-click intervals.	NA	Needs high quality data with good linearity and sufficient bandwidth	Evolved from *SPUD* algorithm (more general than *SPUD*).	Blainville's beaked whales, pilot whales, Risso's dolphins (Harland 2008)
SIGNAL	Engineering Design	www.engdes.com	Signal 4.0 $2500, event detector $995, event analyzer $795, single pc licenses	.wav, .aiff, headerless binary format	Easy to learn. Many actions such as opening and displaying a sound file can be performed by using drag and drop. Dialog boxes, keyboard commands, online help. Has it's own programming language to allow users to create their own functions	Yes	Detection based on user-specified spectral, temporal, and amplitude criteria. Can be integrated with user-supplied analysis and measurement of detected events using *SIGNAL* analysis tools.	Spectrogram correlation and statistical analysis and comparison of extracted sound contours	Post-processing only		Also has localization capabilities	Bottlenose dolphins (Janik 1999, Janik et al., 1994), killer whales (Riesch et al., 2006), harbour seals (Van Parijs et al., 2000), Yangtze finless porpoise (Songhai et al., 2007), rhesus monkeys (Le Prell et al., 2002), piglets (Weary et al., 1999), birdsong (Slabbekoorn et al., 2000, Leitner et al., 2001)
TRITON	Marine Physical Laboratory, Scripps Institute of Oceanography	from the author	Free	.wav, .xwav (similar to .wav but contains additional header information)	Creates standard *MATLAB* figure windows with pull-downs and tools that are the same as typical *MATLAB* figure windows, so figures can be modified, saved in various formats and printed. Extensive and helpful users manual, pull-down menus, dialogue boxes, buttons for scrolling through data	Yes	None	None	Post processing only	No automated detection or classification capabilities	Allows quick overview of long-term recordings by creating long-term spectral averages (hours to weeks can be displayed on a single plot). Allows for quick searching for acoustically significant events. Event detection and classification algorithms currently being developed for use with *TRITON*.	Right whales (Munger et al., 2005)
Syrinx	John Burt	Available for download at http://www.*Syrinx*pc.com	Free	.wav, .aif	Easy to learn, no users manual, relatively comprehensive help files	Yes	Simple band-limited energy detector. Detects and stores sounds as individual .wav files.	None	Both	Does not display or measure sound spectrums.	Can be used to measure sounds. Cursor measurements stored to a text file.	Dolphins (Remage-Healey et al., 2006), beluga whales (Belikov and Bel'kovich 2007), birds (Bard et al., 2002, Gammon and Baker 2004, Hill et al., 2006, Sewall and Hahn 2009), fish (Remage-Healey and Bass 2005)
Acoustic Cetacean Detection Capability (*ACDC)*	Defense Research and Development Canada (DRDC)	Contact DRDC		.wav, .wav64, and others	Components can be augmented, customized or reintegrated into custom applications suited to specific requirements	NA	In-band energy detector based on likelihood ratio test	NA	Both	No scrolling spectrogram	Any number of channels can be processed at any sample rate. Provides a summary table of detections and breakdown by category and classification, where available. Graphical and tabular displays of detection features are available. Provides spectrograms and spectra of detections. User can manually annotate and classify detections.	
Biosonar program	W. Elsberry	From the author	With agreement as to credit for collaboration	NA	NA	NA	Detection of echolocation clicks	Classification of echolocation clicks using neural networks	Post processing			**References snd species**
Hound	D. Blackwood	From the author	With agreement as to credit for collaboration	NA	NA	No	Automated detection of whistles based on finding sounds of minimum intensity for a minimum period of time. Eliminates clicks and burst pulses.	None	Real-time		Implemented in Borland's 'Delphi' development environment	Elsberry (2003), Pettis (2004)
JASCO software	*JASCO* Applied Sciences, Halifax, Nova Scotia	ongoing development - contact *JASCO* for further details	NA	.wav	under active development in *MATLAB*, currently no GUI or documentation.	Yes	Detection using a split window normalizer and detections summed across frequency bands.	Classification based on cepstral coefficients and Gaussian Mixture Models. Includes fin whales, bowhead whales, killer whales, beluga whales, gray whales, bearded seals, and walrus	Post processing	Currently under development		Blackwood (2003)

6 Figures

		Actual Value	
		p	n
Predicted Value	p	True Positive	False Positive
	n	False negative	True negative

Figure 1. Example of a confusion matrix

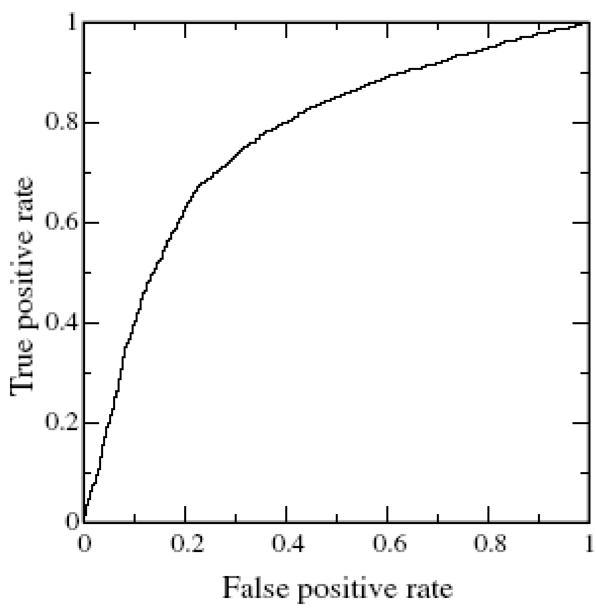

Figure 2. Example of a Receiver Operating Characteristics (ROC) curve (from Fawcett 2006).

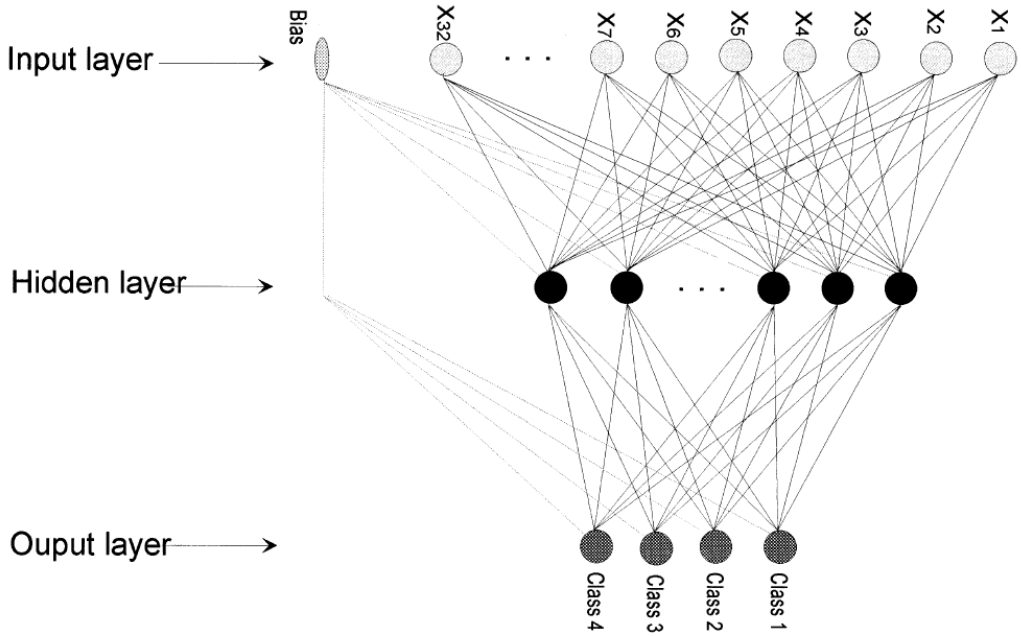

Figure 3. Example of the structure of an artificial neural network (from Reby et al., 1997).

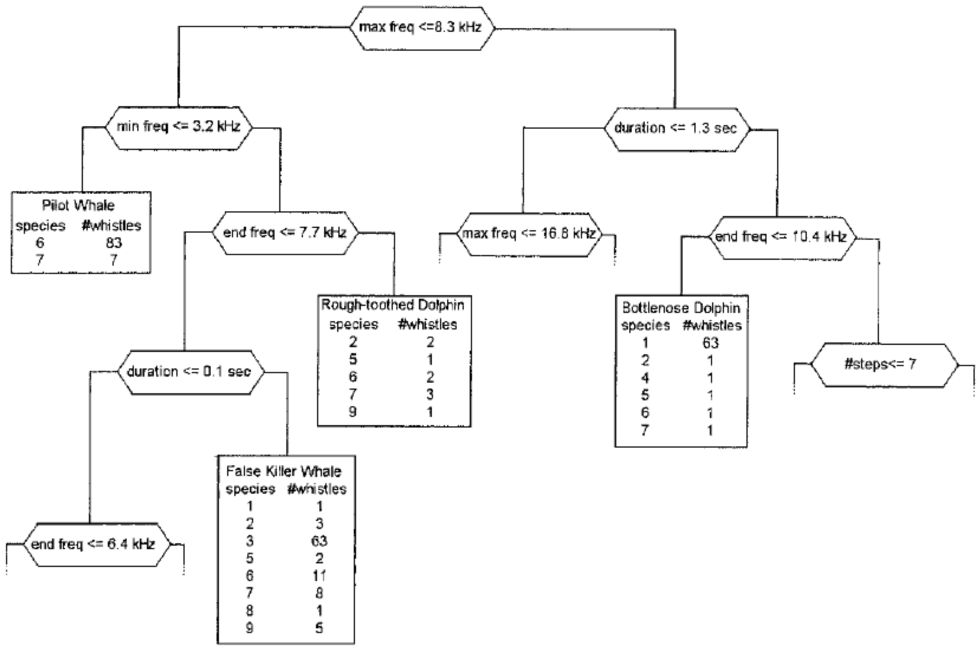

Figure 4. Example of a classification tree (only a portion of the tree is shown). Each split is based on the value of a single variable. Final classification is reached at 'terminal nodes', denoted by squares. Terminal nodes are labeled according to the species with the greatest number of whistles in that node. Species are represented numerically: 1 = *Tursiops truncatus,* 2 = *Delphinus delphis,* 3 = *Pseudorca crassidens*, 4 = *Stenella attenuata,* 5 = *D. capensis,* 6 = *Globicephala macrorhynchus,* 7 = *Steno bredanensis,* 8 = *Stenella coeruleoalba,* 9 = *S. longirostris* from Oswald et al., 2003).

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Appendix A – Localization Capabilites

Table 1. Localization capabilities for software packages reviewed in chapter 3 "A Review of computer-based methods for the automated detection, extraction and classification of marine mammal sounds". This table is not meant to be a comprehensive list of all localization software available, it summarizes those software packages reviewed in chapter 3.

Product name	**Developer**	**Localization Capabilities**	**Real-time/Post-processing**	**Mapping Capabilities**	**References and Species**
Ishmael	Dave Mellinger, Oregon State University	Location of a sound source in one dimension (bearing angles with left-right ambiguity) or two dimensions (X-Y position). Five localization alogoritdhms provided: 1) phone pair bearing calculation: determines a hyperbola on which the sound source lies. Requires multiple bearings for localization (e.g., target motion analysis). 2) Frequency beamforming bearing calculation: uses a delay-and-sum beamforming technique. Works best with many hydrophones, but can be used with as few as two. Most useful when the sound source is relatively far away from the hydrophones. Assumes that the hydrophones are in a straight line. One method available for impulsive sounds and one method available for tonal sounds. 3) Time domain beamforming: another technique for calculating bearings. 4) Hyperbolic calculation (X-Y positions): uses time-of-arrival differences at different hydrophones to calculate the intersection of hyperbolae. Useful when the sound source is near to or inside the hydrophone array. Can also localize in three dimensions (with more than three hydrophones). 5) Crossed-pair localization: requires at least four hydrophones. Calculates a bearing independently from each of two pairs of hydrophones and calculates the intersection point of the bearings as the location of the sound source. Requires a long-baseline array to estimate positions ranging approximately 3-5 times the baseline length.	both	Bearings that lie between 0 and 180 degrees are plotted on a chart. Bearings can also be sent to another program (such as WhalTrak) for mapping.	Dolphins (Rankin et al. 2008), minke whales (Rankin and Barlow 2005, Rankin et al. 2007), right whales (Wiggins et al. 2004), blue whales (Sirovic 2006), fin whales (Sirovic 2006), humpback whales (Miksis-Olds et al. 2008, Smith et al. 2008), harp and weddell seals (Moors and Terhune 2005),

Product name	**Developer**	**Localization Capabilities**	**Real-time/Post-processing**	**Mapping Capabilities**	**References and Species**
Pamguard	Doug Gillespie, Sea Mammal Research Unit, University of St. Andrews; Herriot Watt University; Oregon State University; Scripps Institution of Oceanography; and others	Four localization algorithms available: 1) localizes sounds selected from a spectrographic display or using output from one of PAMGUARDs automated detectors. This method works with a sparse array configuration and requires at least three hydrophones. It can not calculate bearings off of a single pair or closely spaced group of hydrophones. 2) Localization algorithm based on those used in Ishmael and RainbowClick. These methods can determine bearings using closely spaced pairs of hydrophones. Left-right ambiguity will depend on the number and configuration of hydrophones. 3) Click detector: automatically estimates locations from multiple clicks using target motion analysis. 4) 3D localization of pulsed sounds. If accurate hydrophone depth information is available, this algorithm can localize pulsed sounds automatically detected by a click detector. It utilizes surface echos to obtain slant angles for estimating a 3-D location. Requires a long-baseline array to estimate locations ranging approximately 3-5 times the baseline length.	both	Plots bearings and localizations using it's mapping module. Map shows position of vessel, hydrophones, bearing angles and localizations (with left-right ambiguity).	Sperm whales (Gillespie et al. 2008)
Rainbow Click	International Fund for Animal Welfare (IFAW)	Uses time-of-arrival differences at a pair of closely spaced hydrophones to calculate bearing angles to clicks. Multiple bearings requried to obtain localizations using target motion analysis.	both	Interface to "Logger2000", which displays a real-time map of the ships track as well as bearing angles to detections. Logger2000 also saves data to an Access database.	Gervais' beaked whales (Gillespie 2009), sperm whales (Hastie et al. 2003, Drouot et al. 2004, Aguilar de Soto et al. 2004, Lewis et al. 2007), beaked whales, dolphins, and pilot whales (Aguilar de Soto et al. 2004), harbour porpoises (Weir 2008)
Raven	Cornell Laboratory of Ornithology	none	n/a	n/a	n/a
XBAT	Cornell Laboratory of Ornithology	none	n/a	n/a	n/a

Product name	Developer	Localization Capabilities	Real-time/Post-processing	Mapping Capabilities	References and Species
Avisoft SASLab Pro	Avisoft	none	n/a	n/a	n/a
Sound Ruler	Marcos Gridi-Pap, Phys. Science, UCLA	none	n/a	n/a	n/a
ROCCA (Real-time Odontocete Call Classification Algorithm)	Julie Oswald, Hawaii Institute of Marine Biology	none	n/a	n/a	n/a
Leafy Seadragon	Serge Masse	none	n/a	n/a	n/a
Songscope	Wildlife Acoustics	none	n/a	n/a	n/a
MMADS (Marine Mammal Automated Detection System)	Kaon Ltd., jointly with QuinetiQ	Uses range focused beamforming. The system does not try to localize individual animals or calls, but provides information on the highest probability alert. Time-of-Arrival-Difference (TOAD) localization has not been implemented, but may be added in the future.	Post processing	A simple sector based display indicates whether the animals are port, starboard, fore or aft, long or short range.	n/a
SPUD algorithm (Simple Porpoise Underwater Detector)	Edward J. Harland	none	n/a	n/a	n/a
TRUD algorithm (Transient Research Underwater Detector)	Edward J. Harland	none	n/a	n/a	n/a
SIGNAL	Engineering Design	Up through v3, SIGNAL had a full-function localization module based on TOAD derived from spectrogram cross-correlation. Localization graphics wasn't feasible in SIGNAL for Windows, so the current SIGNAL v5 has the mathematical tools for localization without the graphics. SIGNAL would typically write results such as bearing, range, location, etc. to a text file for export virtually anywhere.	Post processing	None	Bottlenose dolphins and harbor seals (Janik et al. 2000)
TRITON	Marine Physical Laboratory, Scripps Institution of Oceanography	none	n/a	n/a	n/a

Product name	**Developer**	**Localization Capabilities**	**Real-time/Post-processing**	**Mapping Capabilities**	**References and Species**
Syrinx	John Burt	none	n/a	n/a	n/a
Acoustic Cetacean Detection Capability (ACDC)	Defense Research and Development, Canada (DRDC)	Yes - further information not available.	n/a	n/a	n/a
Biosonar program	W. Elsberry	none	n/a	n/a	n/a
Hound	D. Blackwood	none	n/a	n/a	n/a
JASCO software	JASCO Applied Sciences, Halifax, Nova Scotia	Yes - under development	Post processing	Under development	Arctic species such as bowhead whales, walrus, and beluga whales (pers. comm.)

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