Passive acoustic detection of modulated underwater sounds from biological and anthropogenic sources

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Abstract—**This paper describes an algorithm for the automatic detection of a particular class of underwater sounds, using a single hydrophone. It is observed that many life-forms, systems or mechanisms emit distinctive acoustic signatures which are characterized by packets of relatively high frequency sound that are repeated at regular, low frequency intervals. These types of sounds are commonly produced by biological (e.g. fishes and invertebrates) and anthropogenic (e.g. scuba diver) sources. The algorithm exploits a simple feature, extracted from the raw hydrophone signal, which enables robust detection even in conditions of severe background noise. In order to demonstrate how the algorithm can be used, trial applications are presented for the detection of two different kinds of underwater sound source. First, the algorithm is applied to the problem of detecting soniferous fish sounds, showing that it is possible to robustly automate the detection of instances of cusk-eel presence in hydrophone recordings, thereby simplifying the arduous task of human monitoring of long sound recordings in marine biological research. Second, the algorithm is applied to the problem of automatic diver detection in a noisy urban estuary, demonstrating its potential for harbor security and fleet protection.**

I. Introduction

This paper presents an algorithm which can be used to recognize the presence of a variety of soniferous entities in passive acoustic signals. It is observed that many life-forms, systems or mechanisms emit distinctive acoustic signatures characterized by packets of relatively high frequency sound that are repeated at regular intervals with a repetition rate of relatively low frequency. Pattern recognition schemes which can make use of both frequencies to characterize an entity are likely to be highly robust against many kinds of background noise, since there is a low probability that another entity will share both frequencies.

We show how a useful feature can be extracted from passive acoustic signals which attempts to evaluate to what extent an object is present which emits regularly repeated packets of sound in a characteristic high frequency range, such that the repetition rate falls within a characteristic low frequency range. Automated detection can be achieved simply by appropriate thresholding of the resulting feature value.

We demonstrate this technique with applications to two very different examples of modulated sound sources, soniferous fish and SCUBA divers. The cusk-eel, *Ophidion marginatum*, is one example of a soniferous fish which can be recognized by its distinctive call consisting of a rapid series of clicks. Each click consists of relatively high frequency sound (order 1KHz), but the clicks are repeated at regular intervals of relatively low frequency (order tens of Hz). In a similar fashion, we note that the primary source of sound emitted by a SCUBA diver relates to the diver's breathing. The breathing sounds occupy a wide frequency spectrum, but are most distinct from background noise in a prominent ultrasonic frequency range. Thus a diver can be characterized by packets of high frequency ultrasound which occur at a low frequency repetition rate, corresponding to typical human breathing rates (around 0.3Hz).

A. Acoustic surveying of soniferous fish

There is increasing interest, amongst the marine biology community, in the use of acoustic surveying techniques for non-invasive population assessments and for the identification of essential fish habitats. Studies of fish sounds can provide a wealth of data on temporal and spatial distribution patterns, habitat use and spawning, feeding, and predator avoidance behaviors, [1], [2], [3]. Unfortunately, acoustic surveying of fisheries is hampered in that it relies on human experts to painstakingly search through many hours of sound recording by hand in order to count the instances of soniferous fish activity. This difficulty has severely limited the scope of previous attempts at acoustic surveying. We demonstrate an application of our passive acoustic detection algorithm to automating the process of searching through lengthy sound recordings to identify instances of fish calling.

B. The diver detection problem

One of the most challenging aspects of port security is providing the means to protect against threats from under the surface of the water, [4]. In particular, it is felt that a significant terrorist threat might be posed to domestic harbors in the form of an explosive device delivered underwater by a diver using SCUBA apparatus, [5]. Although active sonar systems exist

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which can detect and track moving targets, e.g. [6], the problem of recognizing which, if any, moving entities are human divers is less well understood. This recognition problem lends itself to a passive acoustic approach, since these techniques can make use of prior knowledge of the specific sounds generated by a diver. Additionally, existing techniques which rely on active sonar devices may be prohibited in many domestic harbors due to their environmental effects (e.g. disturbance of marine mammals).

II. A SIMPLE PASSIVE ACOUSTIC DETECTION ALGORITHM FOR MODULATED SOUNDS

We address the problem of passively detecting the presence of a class of modulated sound emitting entities which can be characterized by two frequencies. Firstly, these entities emit packets of sound for which energy is either concentrated in, or best dominates noise, over a frequency range, Δf_{high}, about a prominent characteristic high frequency, f_{high}, i.e. the entity signal is most distinct from typical background noise in this range. Secondly, these packets are repeated at regular intervals, such that the repetition rates lie in a lower frequency range, Δ_{flow}, about a characteristic low frequency, f_{low}.

We now describe how to calculate a single feature, which can be used with a simple discriminatory thresholding function to determine entity presence robustly against severe background noise. The feature evaluates to what extent an object is present which emits regularly repeating pulses of sound with a prominent component in the high frequency range, $\Delta f_{high,}$ and with a pulse repetition rate in the low frquency range, Δf_{low}. The feature calculation process is summarized in figure 1.

Firstly the raw hydrophone signal is narrow bandpass filtered over a small range of frequencies, Δf_{high}, about the characteristic high frequency, f_{high}. Secondly, an envelope is fitted to the filtered signal by connecting peaks and smoothing. Thirdly, the envelope is Fast Fourier Transformed to produce a spectrum for the envelope waveform. Lastly, the spectrum is integrated over the range, Δf_{low}, about the characteristic low frequency, f_{low}, yielding a single characteristic number. This number is discriminating in that it takes high values when the entity of interest is present and low values otherwise, even in severe conditions of background noise.

This feature can be used for detection by means of a simple thresholding process. At any point in time, the entity is considered to be present if the feature value, calculated for the most recent portion of signal, exceeds a critical threshold value. To implement this detection system, only a small number of parameters must be determined from training data: f_{high} and Δf_{high}, f_{low} and Δf_{low}, and an appropriate threshold value. These parameters are obviously application specific. In the following sections we describe how these parameters were estimated for two very different applications.

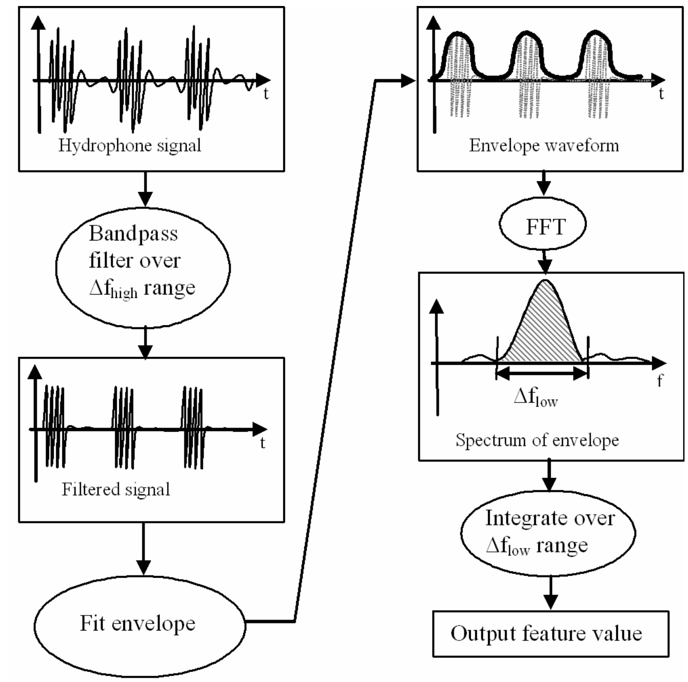

Figure 1. Procedure for extracting a discriminatory feature from hydrophone signals.

III. DETECTING CUSK-EEL CALLS

A. Characterizing cusk-eels

The cusk-eel, Ophidion marginatum, is one example of a soniferous fish which can be recognized by its distinctive call consisting of a rapid series of clicks (maximum number of clicks 73, median 31, [7]). Cusk-eels were recorded in the wild at a sampling rate of 20 kHz using bottom-mounted hydrophones installed at locations identified as potential cusk-eel habitats. Analysis of the soniferous activity of cusk-eels revealed that they tend to emit sound pulses (clicks) of approximately equal amplitude at regular intervals. The cusk-eel calls examined for this paper typically consisted of up to 27 pulses, which tended to be repeated in a characteristic low frequency repetition rate range, Δflow, between 20 and 25 Hz. We note that other researchers have reported somewhat lower repetition rates (18.3 Hz) for cusk-eel sounds based on 164 randomly selected calls, [7]. The discrepancy may lie in the fact that the 20-25Hz, that we report, was measured for 1s duration samples of cusk-eel sound, whereas Mann et al. divide the duration of a complete call (often several seconds) by the total number of clicks in that call (the method typically employed by marine biologists). The discrepancy might possibly be caused by a single cusk-eel call being composed of several packets of 20-25Hz repetition, interspersed with very small delays or short periods of lower frequency. Since this paper addresses the problem of ascertaining whether or not any given 1s period of sound recording contains a cusk-eel call, the use of the 20-25Hz range is preferred. This is important in that the repetition frequency reported by marine biologists may not be the best value to use with detection algorithms.

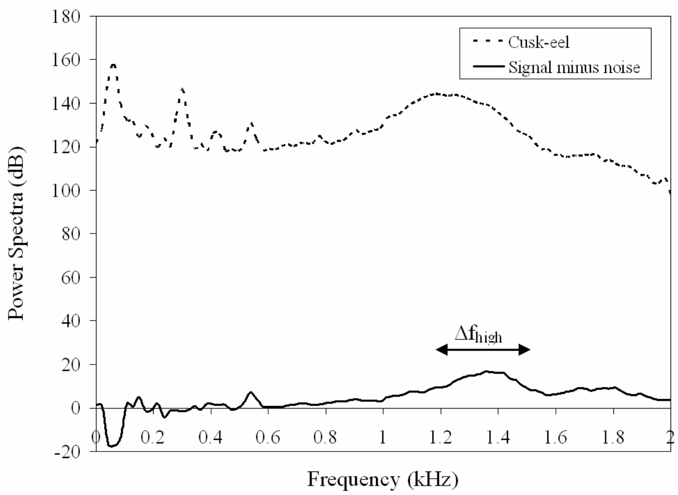

Figure 2. Spectrum for a cusk-eel call compared against typical ambient background noise spectrum recorded in the cusk-eel habitat.

Time-series data, was processed using a fast Fourier transform (FFT) to produce spectra of the cusk-eel calls (figure 2). The spectrum of the call was compared to that of ambient noise in the cusk-eel habitat to identify the prominent frequency range for filtering. It is observed that the cusk-eel signal occupies a broad spectrum but tends to dominate the background noise in a frequency band, Δf_{high}, between 1200 and 1500Hz. Hence the raw hydrophone signals can be band-pass filtered in this range to obtain a time-series corresponding to the highest signal-to-noise ratio (SNR).

B. Calculating a discriminating "cusk-eel number"

We now describe how a hydrophone signal is processed to yield a discriminating feature value, or "cusk-eel number", which correlates with cusk-eel presence. Each of the following steps corresponds to a stage in figure 1. Firstly, the hydrophone signal is band-pass filtered over a frequency range, Δf_{high}, of 1200 to 1500 Hz (figure 3). Next, an envelope of the time

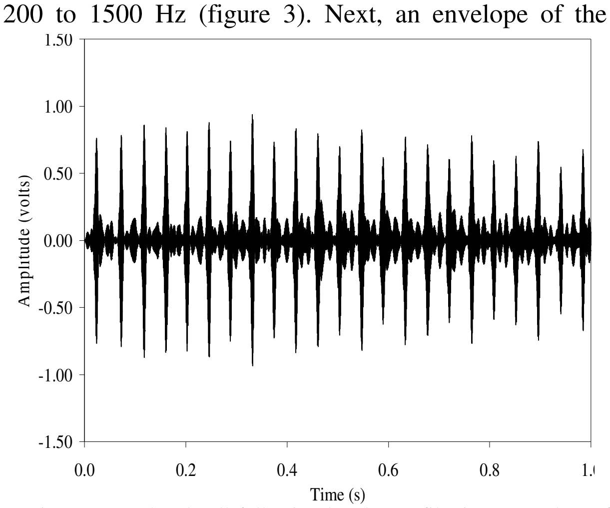

Figure 3. Cusk-eel call following band-pass filtering. 23 pulses of high frequency sound emitted at regular, low frequency intervals.

series signal is calculated by discarding the negative amplitudes, then smoothing by low-pass filtering (figure 4).

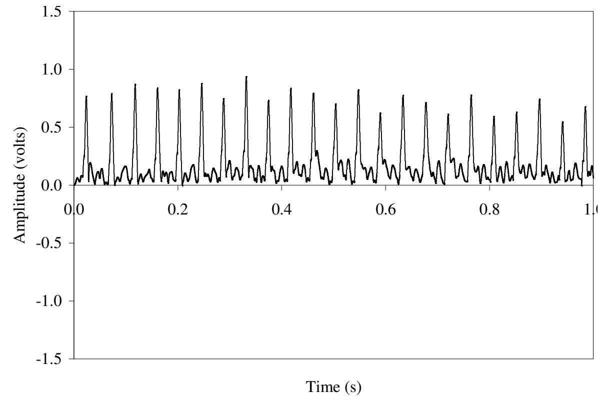

Figure 4. Envelope fitted to filtered hydrophone

The envelope waveform is now Fast Fourier Transformed to give an envelope spectrum (figure 5). For envelopes of cusk-

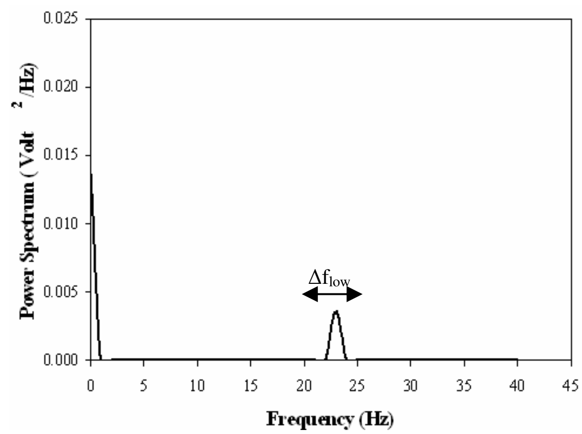

Figure 5. Typical envelope spectrogram for a band-pass filtered cusk-eel call.

eel calls, the energy is highly concentrated in a band of frequencies between 20 and 25 Hz (the frequency at which the characteristic cusk-eel clicking sounds are repeated). Note that the large signal, close to zero frequency, is a DC level resulting from the demodulation process, and can be ignored. In

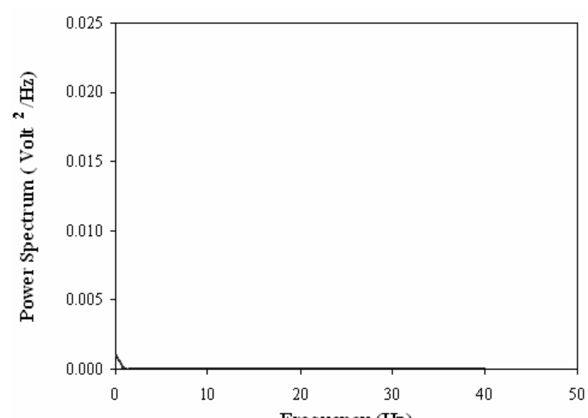

Figure 6. Envelope spectrogram for band-pass filtered ambient noise in a cusk-eel marine habitat.

contrast, performing the same operation (filtering, demodulating and Fourier Transforming) on typical samples of background noise does not yield a concentration of energy in this frequency band (figure 6). Hence this peak is highly discriminatory. There is some variation in the number of characteristic pulses produced per second, both between different cusk-eel calls and also throughout the duration of any particular call ([7] reports a coefficient of variation of 2.8%). Hence the energy associated with a particular frequency, e.g. 23Hz, is not a generalizable feature (may not be appropriate to all cusk-eels). Therefore, to account for the variable nature of cusk-eel calling, we integrate the density function over a range of possible calling rates (Δf_{low}) of 20-25Hz, yielding a single "cusk-eel number". This number is a useful discriminatory feature since it takes large values when cusk-eels are present and low values otherwise.

C. *Choosing a suitable discriminating threshold*

A simple method for automatic detection of Cusk-eel calling is to threshold the cusk-eel number. Any portions of hydrophone signal whose cusk-eel numbers exceed the threshold are now believed to contain samples of cusk-eel calling.

Note, that the correct choice of threshold is not obvious. This choice must always be a trade-off between probability of "false positive" error (indicating a cusk-eel when none is present, likely with low thresholds) and probability of "false negative" error (failing to indicate cusk-eel presence when a cusk-eel really is present, likely with high thresholds). The best trade-off between these two kinds of error will be different for different applications. Marine biologists will often choose to conservatively estimate the number of calls and hence minimize false positives at the expense of a higher false negative rate in order to avoid over-estimating fish activity levels or numbers. However, for home-land defense applications, such as diver detection (see section IV), the opposite is often true – we would rather have some extra false alrms than risk missing a terrorist during a real (but infrequent) attack.

Cusk-eel numbers (feature values) were calculated for 50 sample recordings (1s duration each), labeled by a human expert as containing cusk-eel calls, and 50 additional 1s recordings of ambient noise, without Cusk-eel calls. A threshold was chosen to minimize probability of misclassification over this sample data set.

D. *Automated analysis of a hydrophone recording*

A major obstacle to the application of passive acoustic surveying techniques to fisheries science, is the need for laborious hand analysis of many hours of sound recordings by human experts. In order to facilitate acoustic fisheries surveys, we apply our detection algorithm to automating the detection of instances of cusk-eel calling in extended hydrophone recordings of soniferous fish activity (figure 7).

A sixty second sample of hydrophone recording was processed by machine, based on the cusk-eel number parameters and threshold obtained in sections IIIA, IIIB and IIIC. The computer was tasked with determining whether or not each one second portion of the recording contained instances of cusk-eel soniferous activity. The output of the automated detection system was compared with similar analysis conducted by a human expert (figure 7). The output of the automated system is largely consistent with the decisions of the human expert, except for a five second period (35-40 seconds) during which cusk-eel calls were extremely faintly audible at the limit of the sensitivity of human hearing. This seems consistent with the preference of many biologists for conservative identification. As well as assisting with the automation of labor intensive tasks, we envisage that this technique may help benchmark consistent standards for the interpretation of soniferous fish recordings during acoustic surveys.

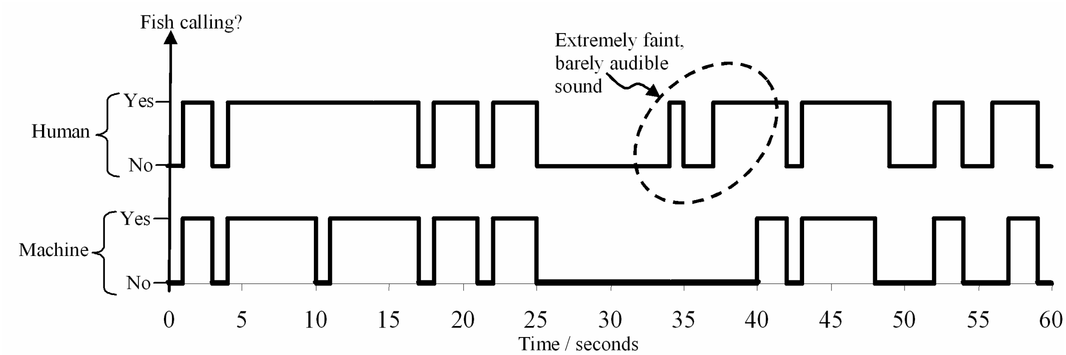

Figure 7. Machine analysis of a one minute segment of sound recording in the presence of soniferous cusk-eels. Comparison with expert human analysis. Note the conservative estimation, i.e. trading off some false negative errors for zero false positive errors in accordance with biologists' measurement preferences. Six misclassifications out of 60 one second samples, all false negative errors.

IV. RECOGNIZING DIVER PRESENCE IN AN URBAN ESTUARY

We now apply the same passive acoustic detection algorithm to the very different problem of automatically recognizing the presence of SCUBA divers in a noisy urban estuary, addressing counter-terrorism concerns for port security and fleet protection.

A. *Measuring the acoustic signature of a diver*

A number of experiments have been carried out to investigate the acoustic signature of a diver and to identify important characteristics of this signature which might be used for the automated recognition of diver presence. Tests were conducted, using our team of expert divers, in the Manhattan region of the Hudson River near the Stevens Institute of Technology (figure 8).

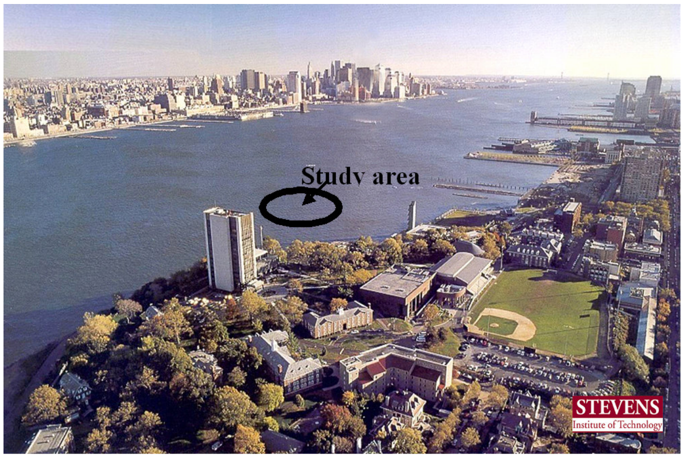

Figure 8 (color online). Stevens Institute of Technology, Hoboken campus and Hudson River where the diver detection tests were conducted.

The depth in the area of the test was between 2 and 3 meters. An omni-directional hydrophone was placed on the river bottom and the diver swam along several paths at different distances from the hydrophone. The diver swam in the middle of the water column at a height 1-2m above the bottom. The diver swam along straight line paths of approximately 40m length, passing the hydrophone at ranges between 1m and 6m. Since the diver paths are known, and the diver was instructed to swim at a constant speed, it is possible to estimate the range from the diver to the hydrophone, for any given portion of the recorded signal. Fig.9 presents the spectrogram of the recorded signal. Bright vertical stripes indicate the acoustic signal produced by the diver, each time he breaths.

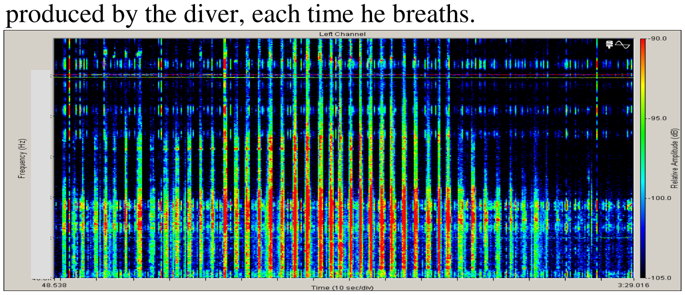

Figure 9. Spectrogram in the frequency band below 100 KHz (Y axis) versus time (X axis). The entire record is approximately 160 sec and the diver moved 40m during this time. The periodic signal of the diver breathing is clearly visible at all ranges from the hydrophone.

The amplitude of the signal increases as the diver swims towards the hydrophone (left half of the figure) and decreases as the diver moves away from the hydrophone (right half of the figure). The periodic signal is clearly visible at all measured ranges (up to 20m) from the hydrophone.

Figure 10 shows the spectrum of the recorded signal for a diver's breathing sound and the difference between this and the spectrum for an example of background river noise with no diver present. Examination of the difference signal indicates that a component of diver sound in a particular frequency range, Δf_{high}, offers the highest signal to noise ratio (SNR). For the purposes of detecting diver presence, it is therefore sensible to filter all hydrophone signals at this frequency, which we will refer to as the "prominent diver frequency".

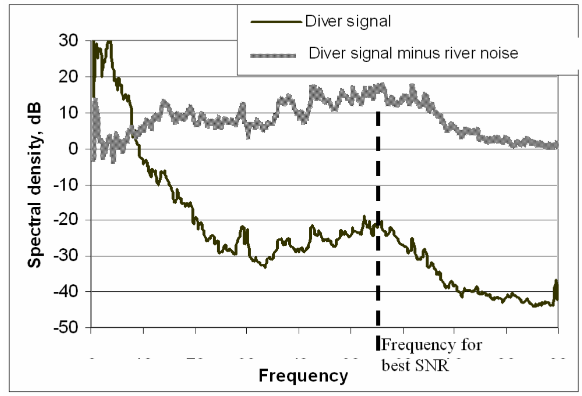

Figure 10. The spectra of the recorded signals for the breathing sound of a diver and SNR in the Hudson River.

B. *Calculating a characteristic number for divers*

We now describe the procedure for computing a highly discriminatory "swimmer number" for diver sounds. Firstly the raw hydrophone signal is band-pass filtered in the prominent diver frequency range, Δf_{high}, in order to improve SNR. Figure 11 shows an example of a hydrophone signal, recorded for a diver in the Hudson River, after band-pass filtering.

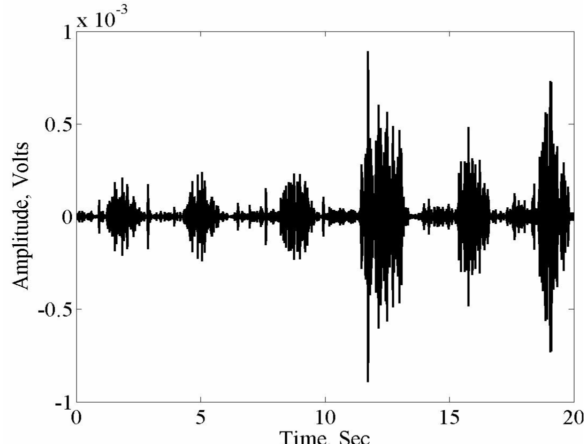

Figure 11. Acoustic signal of a diver, band-pass filtered at prominent diver frequency.

Next, an envelope is fitted to the signal. Negative values are removed and consecutive peaks are connected. The resulting signal is then smoothed by low-pass filtering (figure 12).

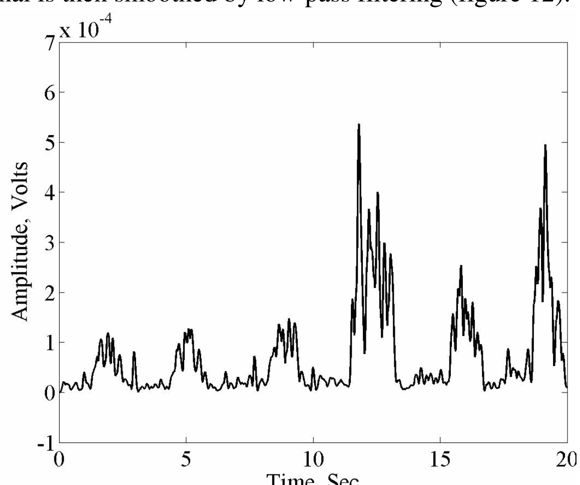

Figure 12. Diver signal envelope.

This envelope is now Fourier transformed to give a spectrum. Figure 13 shows the spectrum of the envelope for an example of a diver in the Hudson River, whereas figure 14 shows the spectrum of the envelope for an example of typical Hudson River background noise with no diver present.

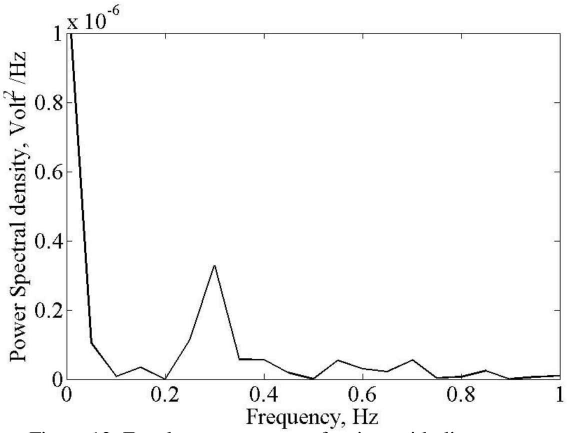

Figure 13. Envelope spectrogram for river with diver present.

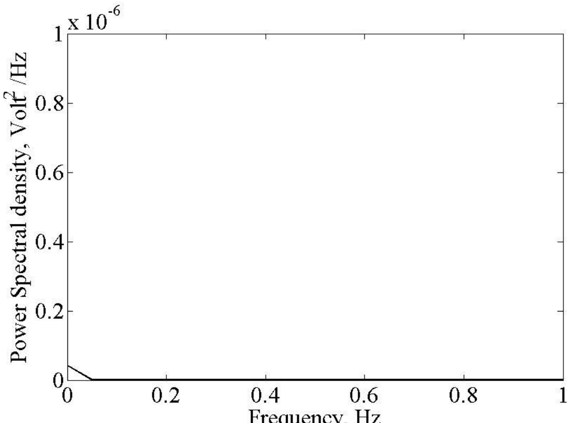

Figure 14. Envelope spectrogram for typical river noise with no diver present.

In signals recorded with a diver present, there is clearly a cluster of energy around the diver's breathing frequency (around 0.3 Hz or about three breaths per second) which is not present in background river noise. This gives rise to a useful discriminating feature. We can now integrate over a likely range of human breathing rates to give a single characteristic number, the "swimmer number", for divers.

Integrating over a range of frequencies is useful since it enables generality, i.e. the algorithm can cope with divers who breathe at a variety of different rates. It should be noted that generality comes at a cost. By integrating over a range of possible breathing rates, we sacrifice optimal detection performance for any specific breathing rate. In terms of detection errors, we are trading off false positives (claiming that there is a diver present when there is not) and false negatives (failing to detect a diver when one really is present). This trade off can be adjusted by adjusting the range of integration. In this paper, for proof of principle, we have integrated over the range 0.2 to 0.4 Hz.

C. *Variation of swimmer number with range and noise level*

The swimmer number, calculated by integrating the spectrum of the hydrophone signal envelope, is useful as a discriminating feature, in that it takes large values when a swimmer is present and small values when no swimmer is present, even in the presence of noise. This leads naturally to a simple algorithm for automatic diver detection. At any instant in time, the previous few seconds of hydrophone signal are used to calculate a swimmer number value. The swimmer number is then compared against a threshold. Swimmer numbers above the threshold are classified as indicating diver presence, those below are classified as indicating no diver presence. Care must be taken when choosing this threshold value since threshold choice, background noise levels and maximum detection range are all closely related.

Swimmer number values were calculated for samples of hydrophone data featuring a diver in the Hudson River. It has been possible to estimate the range from the diver to the hydrophone for each sample (see section A). We can thus estimate the fall off in swimmer number with range (figure 15). It is convenient to work with the logarithm of the swimmer number values, giving a log(swimmer number) plot, expressed in dB scale.

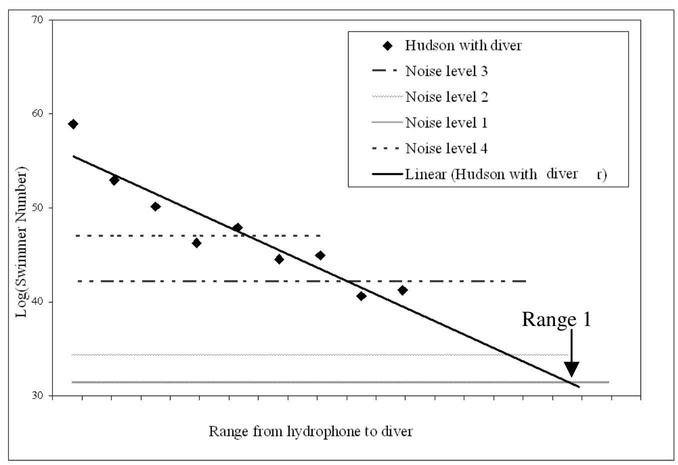

Figure 15. Drop off in log(swimmer number) value with range. Comparison with log(swimmer number) calculated for various ambient noise conditions. Noise level 1: River noise with low traffic levels, at night time. Noise level 2: River with ferry and helicopter noise. Noise level 3: Rough surface conditions, large waves and two helicopters present. Noise level 4: Severe background noise sources including airplane and helicopter traffic, speed boat and ferry.

Superimposed on this plot (figure 15) are the log(swimmer number) values for various samples of background noise for which no diver was present. Extrapolating the plots provides information about the maximum range at which a diver can be detected. If a discriminating threshold is set to a value just above the swimmer number value for "Noise level 1", we might expect "Range 1" to be the maximum range at which a diver can be detected. However, recent work, [8], shows that, in theory there is a 50% probability of detection at this range, and significant detection probabilities at greater ranges.

In practice it may be necessary to use a more conservative threshold to ensure robustness to noise levels which vary considerably in an urban harbor environment. Again, there must be a design tradeoff between extending the maximum detection range and achieving robustness of detection decisions at lesser ranges. To investigate variation of detection ranges and appropriate threshold levels with noise levels, swimmer numbers were calculated for various kinds of background noise which are present intermittently in the Hudson River (see figure 15). During occasional episodes of extreme background noise (e.g. "airplane, helicopter, speed boat and ferry") the possible detection range is considerably reduced. However, it should be noted that these levels of noise are so extreme as to prohibit conversation between two personnel standing together on a boat during these conditions.

V. CONCLUSIONS AND DISCUSSION

This paper has demonstrated an algorithm for automatic passive acoustic detection and identification which can be applied to a variety of underwater entities which emit repeated pulses of sound.

The algorithm has been demonstrated with two very different applications. Firstly, measurements of the vocal activity of soniferous fish in their natural habitat field conditions have yielded algorithm parameters that enable the automated analysis of large amounts of hydrophone data to facilitate acoustic surveying of fisheries. Not only does the algorithm provide a means of automating labor intensive analysis tasks, but it also offers a means of benchmarking uniform standards for analysis of acoustic survey data which until now has been dependent on relatively subjective human analysis. Secondly, diver characteristics have been derived from a series of experiments, measuring the acoustic radiation from divers in the Hudson River. Extensive measurements of a variety of noise conditions in the river have also been collected. Exploiting these characteristics, we have determined suitable algorithm parameters which enable robust detection of the presence of a diver from a single, passive hydrophone signal, in an extremely noisy urban estuary environment.

Future work will seek to enhance detection performance using both hardware and software. We are presently performing experiments to explore the use of beam-forming multiple hydrophone arrays to suppress various kinds of noise. It is thought that this may prove particularly useful for reducing sources of noise such as waves and wind. Secondly, the application of various signal processing techniques may improve detection range. These include incorporating the use of matched filtering techniques and also noise suppression techniques based on understanding of the spectra, directivity and correlation properties of common noise sources. Thirdly, the discriminating feature, presented in this paper, might be combined with other kinds of features, enabling more robust discrimination techniques in high dimensional feature spaces.

Intermittent episodes of extreme noise remain problematic. We can either settle for a conservative (high valued) discrimination threshold (severely reducing the detection range), or we must expect occasional "false positive" detection errors (i.e. noise levels trigger the detection system when no diver or fish is present). One approach to this difficult problem would be an adaptive threshold, i.e. an algorithm which continually adjusts the threshold in response to varying noise levels. A second approach is to explore other pattern recognition approaches for recognizing signals from common noise sources in the river environment (e.g. motor boats, aircraft etc.). This would enable extended detection ranges from low threshold values while eliminating many of the resulting false positive detection errors by recognizing them as common noise sources.

A limitation of the diver detection application is that detecting diver presence is contingent on a relatively long segment of hydrophone signal. Since our algorithm attempts to identify packets of sound which occur at the diver's breathing rate (approximately one breath every three seconds), each swimmer number must be derived from at least 6s of sensor signal. The diver detection results described in this paper were derived using 10s portions of signal. This poses a problem of localization, i.e. the diver may change his position during the detection process. However, the focus of this work is addressing the problem of sound source presence (distinct from the additional problem of estimating sound source position). This work might conceivably be combined with additional techniques in order to also track the trajectory of a sound source. Additionally, our expert divers have reported the need to move very slowly in the turbid and cluttered river environment, with typical speeds of around $0.3ms^{-1}$, causing perhaps ±1.5m error on position measurements derived from 10s of hydrophone signal, a reasonable and realistic level of accuracy for a difficult, noisy environment. This issue is less significant in the fish detection problem, since the more rapid pulse repetition frequency (20-25Hz) enables detection from much shorter samples of signal (0.15s).

For a discussion of how this work may be extended to solve problems of localization and tracking of moving targets, see [8].

A limitation of the soniferous fish application is that, while this work enables the identification of the presence of soniferous fish calling at any given instance, the more difficult problem of automated identification and counting of complete calls has not yet been addressed.

Further investigations are necessary of the response of this algorithm to scenarios involving multiple divers or several simultaneous fish vocalizations. It is worth noting that far greater diver detection ranges might be possible in quieter waters. The noise problems addressed in this paper are extreme and could be viewed as a worst case scenario.

We also plan to carry out more extensive investigations of the acoustic signatures of the objects of interest. For diver detection we are investigating the variation of acoustic signature with different types of SCUBA equipment, different ranges and orientations of the diver to the hydrophone, different individual divers and different diver breathing rates. For fish recognition, we will extend our pilot study of automated cusk-eel detection, exploring the sensitivity of detection techniques to the number of call pulses, call duration, and pulse repetition frequency. For both applications, it is hoped that future investigations may reveal additional useful features, enabling more robust detection.

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