DETECTION OF COHERENT BIOACOUSTIC SIGNALS IN UNDERWATER NOISE

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Abstract: *Challenges in signal detection in the presence of noise arise in many underwater acoustic applications such as active and passive sonar, geophysical surveying, and marine life monitoring. The detection problem is generally formulated within the framework of binary hypothesis testing. An important class of detectors, known as the locally optimum detectors, are designed based on the expectation that the signal of interest is relatively weak compared to noise. The West Indian manatee, added to the endangered species list in 1967, can be routinely found in the shallow Florida waterways and channels. These waterways are heavily utilized by recreational boaters, and a majority of the unnatural manatee deaths are attributed to watercraft collisions. Another major underwater acoustic noise source in Florida channels result from shrimp crackles. Recent research effort has been directed towards developing and implementing advanced signal processing techniques for far range passive acoustic detection of manatee vocalizations. In this paper, the problem of detecting manatee vocalizations in noisy underwater acoustic environments is addressed. Manatee vocalizations are modelled as narrowband, autoregressive, harmonic signals, and boat noise is modelled as a Gaussian process. Two impulsive noise models, the Middleton Class-A and the SαS PDF model for snapping shrimp crackles are investigated. Locally optimal or suboptimal detectors for each noise case are implemented in the form of Gaussian-Gaussian mixture and the Cauchy locally optimal detectors. The performance of these detectors is evaluated through Monte-Carlo simulations and results indicate that the locally optimum Gaussian detector outperforms the non-Gaussian detectors, even when noise contamination is significantly impulsive.*

Keywords: *underwater acoustics, weak signal detection, bioacoustics.*

1. INTRODUCTION

Passive acoustic methods have emerged as the primary means of monitoring marine mammals, particularly, species facing extinction. These methods have several advantages over other means of monitoring in that they enable remote monitoring at far distances with minimal impact on the habitat of the creatures. Furthermore, they permit monitoring in habitats hostile to humans such as deep oceans, making them very suitable for marine mammal monitoring. Passive acoustic monitoring can involve detection, localization and tracking, generally in this order. Thus, detection is a prerequisite in most passive acoustic algorithms and successful acoustic monitoring requires effective acoustic detection.

Marine mammals have different characteristic vocalizations that must be modelled differently. While detectors that extract calls of different species that exhibit common signal characteristics exist [1], it is generally not possible to design a unifying detector for all marine mammals. This has led to the development of ad-hoc detectors tailored for a species [2]. However, one can attempt to design the detectors within the generalized theory of signal detection and make minimal species specific, design assumptions. Another and perhaps a more important factor in detector design is the noise model. Noise is generally ignored or overlooked in detector designs for marine mammals. While this is an intuitive and acceptable assumption in deep ocean acoustics, it results in non-optimum detectors in shallow waters where the noise model significantly diverges from a Gaussian distribution.

The primary marine mammal of interest in this paper is the West Indian manatee. Detailed mortality statistics of the West Indian manatee have been kept since 1974. Despite measures taken, a majority of unnatural manatee mortalities are attributed to manatee-watercraft collisions. One immediate application of automatic detectors may be the real-time detection of manatee vocalization in the presence of boat and natural ambient noises in order to inform boaters of the presence of manatees in the vicinity. Accordingly, the vocalization of the West Indian manatee is selected as the target signal in the remainder of this paper. Manatee vocalizations are generally harmonic signals with a fundamental and at least two additional harmonics within a band of 24 kHz. In general, the fundamental is located at 3 kHz but can vary from 600 Hz to 5 kHz, but the first harmonic is more dominant compared to the fundamental. The vocalizations typically last between 0.2-0.5 s.

Research on signal detection beginning in the early 1960s has led to the wealth of literature in the field of noise models, arrays, multi-channel signal processing, and beamforming. Recent years have brought about an increased interest in utilizing these concepts from this well developed field for passive acoustic detection of marine mammals. The matched filter or the linear correlator (LC) is the universally most powerful (UMP) detector for a target signal in the presence of white Gaussian noise and was used for automatic detection of certain cetacean species in [3], and in part in [4]. In [5], a spectrogram correlator was used to detect bowhead whale vocalizations. The spectrogram correlator is the generalized correlator portion of the single channel locally optimum (LO) detector for signals in independently and identically distributed (i.i.d). Gaussian noise [6]. This LO detector reduces to the generalized energy detector for an i.i.d. signal and has been implemented in the frequency domain for detection of various harmonic vocalizations [1, 2, 7]. Signal detection theory was most effectively used in [8], in which parametric models for the target signals were generated and maximum likelihood (ML) estimates of these parameters were utilized, resulting in a generalized likelihood ratio test (GLRT). The background noise model was justified to be Gaussian, resulting in a matched filter detector. The next section introduces the basic concepts of detection theory and LO detectors. To the authors' best knowledge, this paper represents the first attempt to develop such detectors optimized under the constraint of physically and/or mathematically justified noise models designed to detect underwater bioacoustic signals in real-time.

2. THEORY

Following the general linear model of estimation theory, the observations $\mathbf{z} = \begin{bmatrix} z(1) & z(2) & \cdots & z(N) \end{bmatrix}^T$ can be expressed as the additive process given in Eq. (1) where $\mathbf{s}$ is the target signal, $\mathbf{v}$ is the noise vector; and θ is the signal strength parameter.

$$\mathbf{z} = \theta \mathbf{s} + \mathbf{v} \tag{1}$$

The signals that fall within the scope of this paper can be assumed to be zero mean (i.e., $E[s]=0$, $E[v]=0$). Without the loss of generality, it is assumed that both the signal and noise are of unit variance (i.e., $E[s^2]=1$, $E[v^2]=1$) and that the SNR is controlled by the parameter θ. The problem of signal detection is conveniently formulated within the framework of binary hypothesis testing with a simple null hypothesis (H) and a composite alternate hypothesis (K) as shown in Eq. (2).

$$\begin{aligned} H &: f_z(\mathbf{z} \mid \theta = 0) = f_v(\mathbf{z}) \\ K &: f_z(\mathbf{z} \mid \theta \in \Theta_K) = E_s[f_{\mathbf{v}}(\mathbf{z} - \mathbf{s})] \end{aligned} \tag{2}$$

where , f_v is the noise probability density function and $E[\cdot]$ is the expectation operator.

If the alternate hypothesis were to be simple as well (i.e., $\Theta_K = \{\theta_K\}$) in Eq. (2), UMP detectors could be formulated as the likelihood ratio of the hypotheses. These detectors are optimum in the sense that they maximize the probability of detection p_d at a given false alarm rate p_f. Under the composite alternate hypothesis assumption, the likelihood ratio does not result in a UMP detector, except for the case of Gaussian noise. However, if the alternate hypothesis parameter is limited to values within the very near vicinity of the null hypothesis parameter, then UMP detectors for the limited set of alternate hypothesis parameters can be developed. These detectors can be formulated using the generalized Neyman-Pearson lemma and are termed the LO detectors. In that case, the derivative of the alternate hypothesis PDF replaces the alternate hypothesis PDF itself. For i.i.d. noise, the resulting detector is a function of the expectation of the target signal, and under the assumptions of this paper, vanishes for all θ. In that case, the most significant non-zero term of the Taylor series expansion, i.e., the second derivative of the alternate hypothesis PDF replaces the alternate hypothesis PDF. The test statistic of the LO detector for zero mean target signals for i.i.d. noise is given in Eq (3)

$$T_2(\mathbf{z}) = \sum_{n=1}^{N} h_{lo}[z(n)] + \sum_{k=1}^{N} \sum_{n=1}^{N} E[s(k)s(n)] g_{lo}[z(k)] g_{lo}[z(n)] \tag{3}$$

where

$$g_{lo}(z) = -\frac{f_z^{'}(z)}{f_z(z)}, \quad h_{lo}(z) = -g_{lo}^{'}(z) \tag{4}$$

are the LO non-linearities.

3. MODELS

Noise generated by the rotating shaft and the collapse of cavitation bubbles in the wake of a boat propeller have typically been modelled as a Gaussian process [10]. Initially, the Middleton A-Class [11], and recently, the SαS densities [12] were proposed to model signals dominated by snapping shrimp crackles. The Middleton A-Class involves an infinite summation of Gaussian PDFs, but can be truncated to a Gaussian-Gaussian mixture (GGM) without the loss of significant accuracy. Furthermore, the LO non-linearity $g_{lo}(z)$ was shown to be unaffected as a result of this truncation [13]. These results can easily be extended and experimentally verified for the $h_{lo}(z)$ non-linearity for LO detectors of zero mean, stochastic target signals. The SαS density provides a more flexible means of modelling the underwater acoustic noise environments. While SαS densities are more accurate than the A-Class densities for modelling impulsive underwater acoustic environments, they conveniently reduce to Gaussian densities when $\alpha = 2$. Thus, they can serve as a unifying framework in developing detectors to be used in shallow underwater acoustic environments. The major disadvantage in working with SαS stems from the fact that they do not possess a closed form PDF. Thus, LO detectors designed for SαS noise utilize analytic non-linearities that result in sub-optimum performance [14]. Several actual underwater acoustic recordings made in Florida were used to verify that the SαS PDF is a more accurate model than the Gaussian and GGM PDFs for modelling both snapping shrimp and boat noise dominated acoustic environments. These tests revealed that the characteristic exponent (α) varied between 1.6-1.99, depending on the type of noise. In [14], the Cauchy PDF model was suggested as a viable alternative to the general SαS model in terms of detection performance. Since the Cauchy PDF possesses an analytic PDF, the performance of its LO detector was further investigated. Three LO detectors, namely the Gaussian LO, the GGM LO detector and the Cauchy LO detector are evaluated in terms of their detection performances. The LO non-linearities of these detectors are evaluated as shown in Eq. (4).

4. DETECTOR PERFORMANCE

The detection performances of the three detectors are evaluated through Monte-Carlo simulations. The background noise is modelled as a symmetric stable random variable with parameters α between 1.6-1.99 and c between 0.005-0.0075. A set of 10 actual manatee vocalizations with a maximum duration of 0.35 s are used as target signals. They are randomly added to the background noise signal that is 5 seconds long. The data is processed as 8192 sample buffers with a sampling rate of $f_s = 24\ \text{kHz}$. Based on the harmonic structure of the vocalizations, a simple generalized correlator is constructed from the AR coefficients of a harmonic signal with a normalized fundamental frequency of 0.125 and two additional harmonics. The strength of the fundamental and harmonics were assumed to be equal to simplify the design. Following the parametric estimate of the PDF, the LO non-linearities were calculated through Eq. (4). While dispersion is a more suitable measure for evaluating the SNR of signals when noise is a stable random variable, it is desired to evaluate the detection ranges of the detectors, which is based on the traditional measure of the SNR. The performance of the Cauchy detector was unstable compared to the other detectors and required significantly more Monte-Carlo iterations for convergence. The Gaussian detector is both the UMP and the LO detector when noise contamination is truly Gaussian. This result is verified as the performance of the Gaussian detector is the best among the three detectors for $\alpha = 1.99$. However, the performance of the Gaussian detector is observed to be better than the other two detectors when noise contamination is non-Gaussian. Several receiver operating characteristic (ROC) curves corresponding to typical α parameters are plotted below in Figure 1 for SNR = 0 dB. Similar results were obtained at different SNR levels. The Cauchy receiver was observed to be significantly more sensitive to the mismatch between the signal and correlator spectra, which possibly resulted in its poor performance.

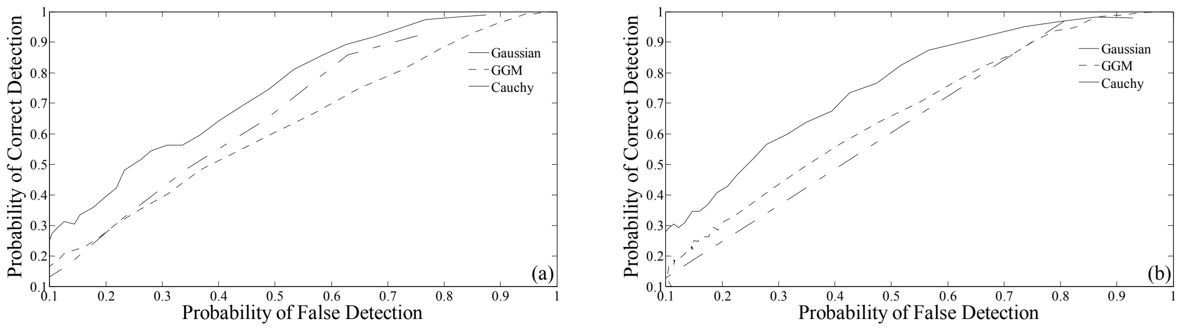

Fig.1: The smoothened ROC curves corresponding to the three detectors for $c = 0.0075$ *(a)* $\alpha = 1.8$*; (b)* $\alpha = 1.6$.

5. CONCLUSIONS AND FUTURE WORK

This paper represents a preliminary study towards the performance of detectors optimized for the detection of weak bioacoustic signals in the presence of Gaussian and impulsive noise. The importance of stable random variables in modelling shallow underwater acoustic environments dominated by snapping shrimp crackles is already acknowledged in several publications (e.g., [12]). However, an additional benefit of the SαS distributions comes from the fact that they can conveniently model Gaussian processes as well. Therefore, stable random variables provide a unifying framework for signal processing, especially in environments when both spiky and Gaussian observations are possible. In this paper, LO detectors for zero mean stochastic signals are developed based on the weak target signal assumption. The detection performances of these detectors are simulated using Monte-Carlo experiments. The Cauchy PDF model is investigated as an alternative to the Gaussian and GGM models since it enables a closed form solution for the second order LO detector. However, the performance of the Cauchy detector was observed to be inferior to the Gaussian based detectors, even under impulsive noise.

The performance of the detectors, in part, depends on the match between the correlator and signal spectrum. While manatee calls in general have well defined harmonic structures and can accurately be modelled as an AR processes, a more detailed model that incorporates time-frequency variations within the call has the potential of improving detection rates. Multi-channel setups can be utilized to improve the detection performance of the LO detectors. However, signals recorded in the presence of moving boats have indicated the presence of a spatial correlation in the observations. Therefore, the spatial correlation might hinder the detection performance of multi-channel setups in the presence of boat noise. This increases the importance of the structure of the correlator and further motivates the future study of efficient correlators.

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