Optimal and Near-Optimal Signal Detection in Snapping Shrimp Dominated Ambient Noise

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***Abstract*—The optimal detection of signals requires detailed knowledge of the noise statistics. In many applications, the assumption of Gaussian noise allows the use of the linear correlator (LC), which is known to be optimal in these circumstances. However, the performance of the LC is poor in warm shallow waters where snapping shrimp noise dominates in the range 2–300 kHz. Since snapping shrimp noise consists of a large number of individual transients, its statistics are highly non-Gaussian. We show that the noise statistics can be described accurately by the symmetric α-stable family of probability distributions. Maximum-likelihood (ML) and locally optimal detectors based on the detailed knowledge of the noise probability distribution are shown to demonstrate enhanced performance. We also establish that the sign correlator, which is a nonparametric detector, performs better than the LC in snapping shrimp noise. Although the performance of the sign correlator is slightly inferior to that of the ML detector, it is very simple to implement and does not require detailed knowledge of the noise statistics. This makes it an attractive compromise between the simple LC and the complex ML detector.**

***Index Terms*—Detection, impulse noise, snapping shrimp noise.**

I. Introduction

Snapping shrimp (family *Alpheus* and *Synalpheus*) produce loud snapping sounds by extremely rapid closure of their snapper claw. The closure produces a high-velocity water jet leading to the formation of a cavitation bubble, which collapses rapidly, causing a loud broadband snapping sound [1]. The shrimp are usually found in such large numbers that there is a permanent crackling background noise in warm shallow waters throughout the world. The snapping shrimp source levels can be as high as 190 dB (peak-to-peak) re 1 μPa at 1 m [2]. At low frequencies, noise from shipping is significant; above $\sim 2\,\text{kHz}$ snapping shrimp noise dominate [3]. As ambient snapping shrimp noise is composed of impulsive noise sources, the resulting noise statistics are non-Gaussian [4], [5].

The problem of detecting a known signal with unknown amplitude in noise is commonly encountered in areas such as communications, target detection, ranging, and environmental sensing. If the noise statistics are known, an optimal detector can be designed based on the maximum-likelihood (ML) criterion. When the noise is Gaussian, the ML detector is the linear correlator (LC) [6]. Unlike a general ML detector, the LC does not require knowledge of the standard deviation of the Gaussian distribution. In the presence of non-Gaussian noise, the LC is no longer optimal. In spite of this, many signal processing algorithms still use the LC for signal detection in non-Gaussian noise due to its simple implementation and the lack of detailed statistical information about the noise.

Since the LC is not optimal in snapping shrimp dominated ambient noise, a significant potential exists for enhancing the detection performance of signal processing algorithms in these waters. Nielsen and Thomas explored the use of nonparametric detectors in snapping shrimp noise [4], however, they concluded that the LC performed better than nonparametric techniques. This conclusion is not in agreement with the results obtained in this paper. More recently, Bertilone and Killeen modeled snapping shrimp noise using a Gaussian–Gaussian mixture, however, they concluded that there were some inconsistencies [7]. They found that locally optimal (LO) detectors performed better than the LC at low signal-to-noise ratios (SNRs) but failed at high SNRs.

In this paper, we show that snapping shrimp noise can be described accurately by the α-stable family of probability distributions. We also demonstrate, via simulation and field experiments, that optimal detectors based on the α-stable distributions perform well in such noise environment, and that the nonparametric sign correlation (SC) detector is a near-optimal alternative. Since the SC detector shares the advantages of the LC detector and yields better performance, it is suited to many signal detection tasks in warm shallow waters.

II. Ambient Noise Statistics

A. Ambient Noise Data

Two data sets collected at different locations in Singapore waters at different times of the year were used as ambient noise samples. At both locations, the water depth is about 15–20 m, the seabed is sandy/muddy and the water is warm (25–30 °C) throughout the year. The data was acquired at a sampling rate of 500 kilo samples per second (kSa/s) using a high-frequency data acquisition system (HifDAQ) [8]. The acquisition system has an analog bandpass filter that allows acoustic data between 1–180 kHz to be recorded. This data was prewhitened using a 64-order digital finite impulse response (FIR) filter. The analysis and results presented in this paper are based on these data sets.

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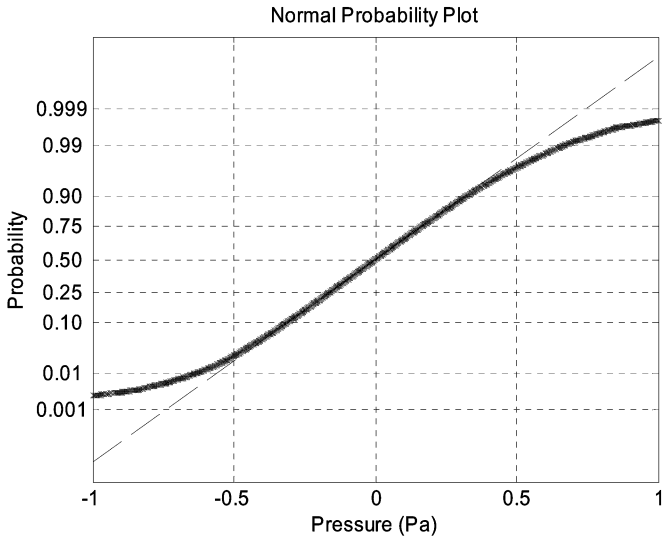


Fig. 1. Normal probability plot of snapping shrimp dominated ambient noise shows heavy-tails.

In addition to these two broadband data sets, lower frequency (1–8 kHz) data collected at many different locations in Singapore waters was used to confirm that α-stable distributions described the data accurately.

B. Non-Gaussian Statistics

In the design of detectors, it is important to take into account the statistics of the noise. The impulsive nature of snapping shrimp sound leads to a non-Gaussian distribution. This is clearly seen from the deviation from linearity in the normal probability plot of the noise (Fig. 1). The snapping shrimp dominated ambient noise has much heavier tails than Gaussian noise. In spite of this clear deviation from Gaussian statistics, it is common to use the Gaussian assumption to simplify signal processing. We show in the following sections that this assumption produces substantially inferior detection performance.

C. The α-Stable Distribution

Impulsive noise tends to produce large-amplitude excursions from the average more frequently than Gaussian signals. The probability density function (pdf) for such noise decays less rapidly than the Gaussian pdf, leading to heavy tails. The family of *stable* distributions provides a useful theoretical tool for such signals [9]. Stable distributions are a direct generalization of the Gaussian distribution and include the Gaussian as a limiting case. The *characteristic exponent* (α) of the distribution controls the heaviness of its tails. A small positive value for α represents highly impulsive distributions while α close to 2 indicates Gaussian-like behavior. When $\alpha = 2$, the distribution reduces to a Gaussian distribution. The stable family of distributions arises from a *generalized central limit theorem*, which states that the sum of independent and identically distributed random variables with or without a finite variance converges to a stable distribution by increasing the number of variables [10]. The defining feature of stable distributions is the *stability property*, which states that the sum of two independent stable random variables with the same characteristic exponent is stable with the same characteristic exponent [9].

The stable distribution is described by four parameters: The characteristic exponent (α), the scale parameter (γ), the location parameter (a), and the symmetry parameter (β). An important subclass of the α-stable distributions, known as the symmetric α-stable $(S\alpha S)$ distribution is characterized by $a = 0$ and $\beta = 0$. The $S\alpha S$ distribution can be most conveniently described by its characteristic function [11]

$$\varphi_\alpha(\theta) = \exp(-\gamma|\theta|^\alpha). \tag{1}$$

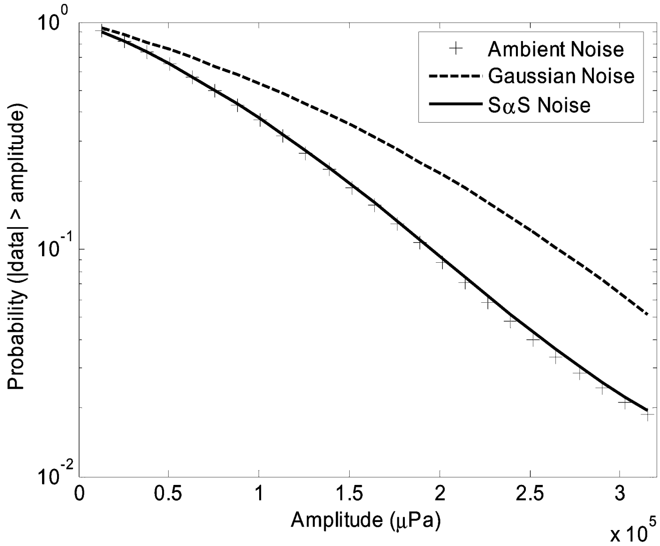
In the previous expression, α is the characteristic exponent controlling the heaviness of the tails. The scale parameter (γ), also known as *dispersion*, determines the spread of the distribution in a similar way to the variance in a Gaussian distribution. When $\alpha = 2$, γ equals half the variance. For all other values of α, the variance of the stable distribution is infinite. A related parameter often used with stable distributions is c (defined as $\gamma^{1/\alpha}$), which plays the same role as the standard deviation for Gaussian random variables. The pdf of the $S\alpha S$ distribution can be computed from the characteristic function [12]

$$f_\alpha(x) = \frac{1}{2\pi}\int_{-\infty}^{\infty} \varphi_\alpha(\theta) e^{i\theta x} d\theta. \tag{2}$$

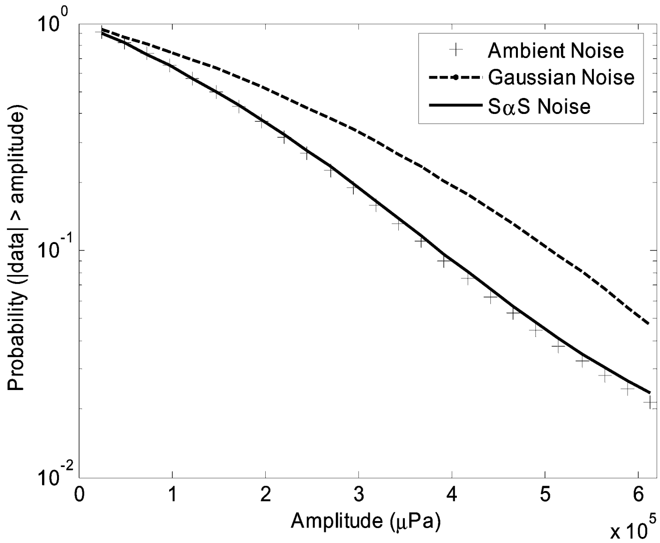
Unfortunately, no closed form expression exists for the general $S\alpha S$ density and distribution functions, except for the Gaussian $(\alpha = 2)$ and Cauchy $(\alpha = 1)$ cases. However, there are efficient numerical methods for computing the pdf [13].

We now describe the procedure to model ambient noise using the $S\alpha S$ distribution. For an acoustic signal, the mean noise pressure must be zero; hence, the location parameter for the distribution must also be zero. The other parameters of the distribution have to be estimated. Several estimators for the parameters of the $S\alpha S$ have been developed [9]. Of these, fractile-based estimators are easy to use and are known to be robust. A p-fractile $(0 \le p \le 1)$ is defined as the value larger than or equal to $p \times N$ observations from a set of N observations. Fractile-based estimators use various p-fractiles of the observed samples to estimate the parameters of the underlying distribution. To estimate the noise parameters, we use a fractile estimator for α developed by McCulloch [14] and a fractile estimator for c developed by Fama and Roll [15]. The $S\alpha S$ fit for noise samples from various locations in Singapore waters were very good, with typical values of α in the range of 1.6–1.9. The value of c is dependent on the bandwidth of the recorded signal. For a bandwidth of 200 kHz, typical values of c were in the range of 50 000 to 150 000 μPa. Sample $S\alpha S$ fits for two ambient noise samples from two different locations are shown in Fig. 2. The Gaussian fit is also shown in the same figure for comparison. The deviation of the data from the Gaussian is highly systematic and cannot be attributed to sampling.

A Kolmogorov–Smirnov test [16] was applied to 10 000 samples randomly chosen from the data to test the goodness of fit of the specified probability distribution to the data. The hypothesis that the data was obtained from a Gaussian distribution was



(a)



(b)

Fig. 2. Amplitude probability plot of snapping shrimp dominated ambient noise showing that the probability distribution can be well approximated using $S\alpha S$ distribution. (a) Location 1 (fit parameters: $\alpha = 1.86$, $c = 7.9 \times 10^4$ μPa). (b) Location 2 (fit parameters: $\alpha = 1.82$, $c = 1.5 \times 10^5$ μPa).

rejected for both data sets at a 1% level of significance. The hypothesis that the data was obtained from an $S\alpha S$ distribution was accepted for both data sets at a 1% level of significance. Similar tests for lower frequency data from other parts of Singapore waters led to the same conclusion.

III. Parametric Detection

Having modeled the ambient noise using an $S\alpha S$ distribution, we can estimate its parameters using the fractile estimators. Once the noise distribution is known, optimal detectors can be designed. As the pdf of the $S\alpha S$ distribution does not have a closed form solution, the detectors make use of the numerical approximations of the pdf. Two optimal parametric detectors are described below.

A. Maximum-Likelihood Detector

An ML detector can be developed for signals of arbitrary strength in $S\alpha S$ noise. Letting $s(t)$ be the signal, A the signal strength and $n(t)$ the noise, the observed data $x(t)$ can be written as

$$x(t) = As(t) + n(t). \tag{3}$$

Given the noise pdf $f_n(n)$ of $n(t)$, a likelihood ratio function L can be written as a function of the estimated signal strength A

$$L = \frac{\prod_t f_n[x(t) - As(t)]}{\prod_t f_n[x(t)]}. \tag{4}$$

Maximizing the likelihood ratio L, or equivalently, minimizing the negative log-likelihood ratio $\tilde{L}$ then gives us the best estimate of signal strength $\hat{A}$

$$\tilde{L} = -\log L = -\sum_t f_n[x(t) - As(t)] + \sum_t f_n[x(t)]$$
$$\hat{A} = \arg\min_A \tilde{L}. \tag{5}$$

The estimated signal strength is expected to be close to zero when no signal is present.

In the case of the $S\alpha S$ distribution, the minimization of $\tilde{L}$ does not yield a closed-form solution in general. Numerical minimization of $\tilde{L}$ leads to an optimal estimate of signal strength, but typically is computationally intensive. Although its computational complexity makes the ML detector impractical for most real-time applications, we use the ML detector as a benchmark for the performance of other detectors in ambient noise.

For the special case of $\alpha = 2$, the $S\alpha S$ distribution reduces to a Gaussian distribution and the minimization in (5) results in the familiar LC estimator

$$\hat{A} = \frac{\sum_t x(t)s(t)}{\sum_t [s(t)]^2}. \tag{6}$$

B. Locally Optimal Detector

The development of detectors in the presence of $S\alpha S$ noise has been investigated by several researchers [6], [9], [17]. A globally optimal (commonly known as *uniformly most powerful* or UMP) receiver does not exist in the general case. However, locally optimal receivers can be designed for the detection of weak signals by introducing a nonlinear transfer function before a standard LC detector. The nonlinear transfer function $g(x)$, can be determined from the noise pdf $f_\alpha(x)$

$$g(x) = \frac{-1}{f_\alpha(x)} \frac{\partial f_\alpha(x)}{\partial x}. \tag{7}$$

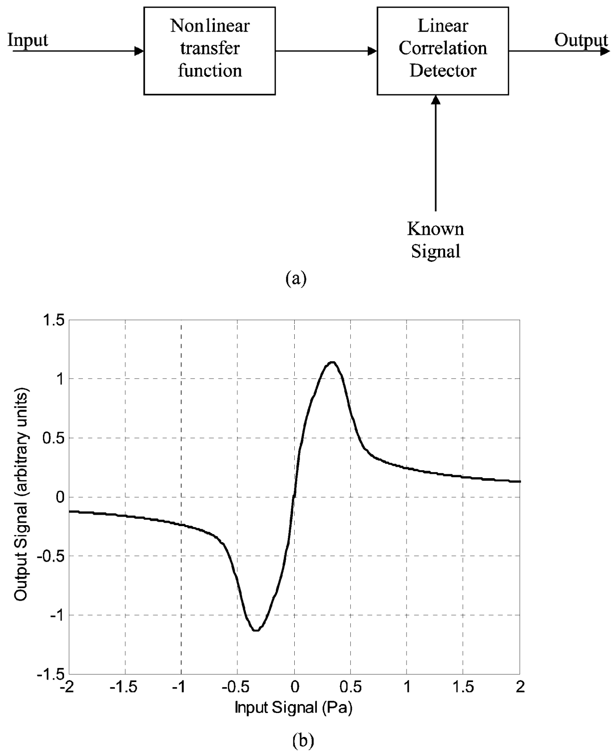


Fig. 3. (a) Structure of a locally optimal detector in $S\alpha S$ noise. (b) Sample nonlinear transfer function for a locally optimal detector in $S\alpha S$ noise.

Since $f_\alpha(x)$ is not available in closed form, we resort to numerical methods to compute the transfer function. The structure of the detector and a typical transfer function for $S\alpha S$ noise is shown in Fig. 3. For small values, the transfer function is approximately linear. For large values, the transfer function vanishes. The improved performance of the LO detector can be understood by observing that the transfer function retains weak signals with minimal distortion while suppressing large amplitude noise.

IV. Nonparametric Detection

Parametric detection schemes require that the statistical distribution and parameters of the noise be determined before detection. On the other hand, nonparametric detectors are designed without knowledge of the exact noise distribution. Although this can be considered an advantage, we expect a penalty in performance resulting from the lack of detailed information of the noise distribution. Nonparametric detectors are often useful when it is not possible or convenient to determine the noise distribution before detection.

The SC detector is obtained by the introduction of a simple nonlinearity (the sign function, sgn) before the standard LC estimator. The denominator of the LC estimator (6) is simply a scale factor and, therefore, can be dropped. The output of the SC detector is thus given by

$$T = \sum_t \operatorname{sgn}[x(t)]s(t) \tag{8}$$

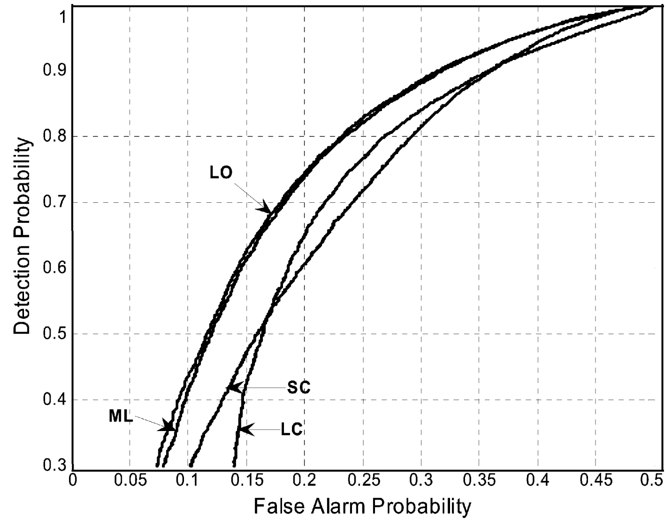


Fig. 4. Detection curves for ML, LO, SC, and LC detectors at SNR of 5 dB.

where

$$\operatorname{sgn}(x) = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{if } x = 0 \\ -1, & \text{if } x < 0. \end{cases}$$

The SC detector is a locally optimal detector in double exponential density noise and also exhibits robust performance in many other types of non-Gaussian noise [18]. It is an attractive detector since it is nonparametric and numerically very simple to implement.

V. Detector Performance

A. Numerical Simulation

We tested the effectiveness of LC, ML, LO, and SC detectors for detecting a signal in additive ambient noise using Monte Carlo simulations with 50 000 iterations. During each iteration, a direct-sequence spread spectrum signal (50-kHz center frequency, 15-kHz spread, 2-ms length) was randomly added to a recorded ambient noise sample ($\alpha = 1.91$). The detection performance of the detectors was then computed based on their ability to correctly determine the presence or absence of the signal. The simulations were repeated for varying values of signal strength to test performance as a function of SNR. Usually SNR is defined as the ratio of the signal power to noise power. Since $S\alpha S$ noise has theoretically infinite variance and hence infinite power, the usual definition of SNR is not meaningful for our analysis. We adopt the ratio of signal power to noise dispersion as a measure of SNR [9] since dispersion plays a similar role in $S\alpha S$ noise as variance does in Gaussian noise. When $\alpha = 2$ and the $S\alpha S$ noise reduces to Gaussian noise, the dispersion is equal to half the variance.

Fig. 4 shows the detection curves for the detectors at a low SNR of 5 dB. It is clear that the ML and LO detectors display the best performances with the SC detector slightly worse than these optimal detectors. The LC detector is the worst as it is unable to achieve low false alarm probabilities (P_{FA}). At high P_{FA}, the LC detection probability is sometimes slightly better

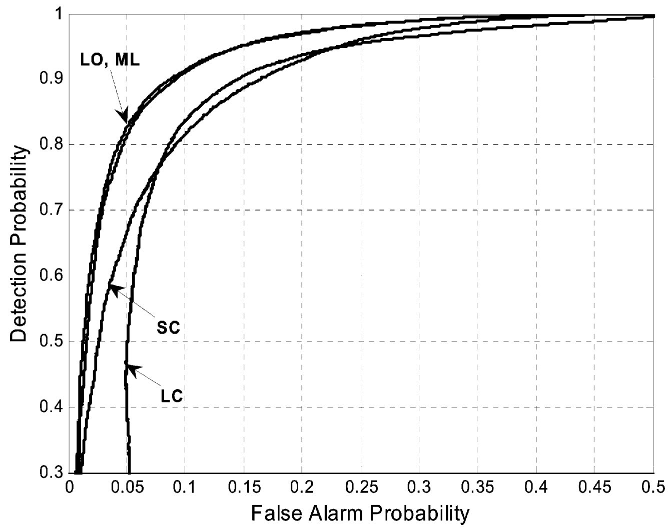


Fig. 5. Detection curves for ML, LO, SC, and LC detectors at SNR of 10 dB.

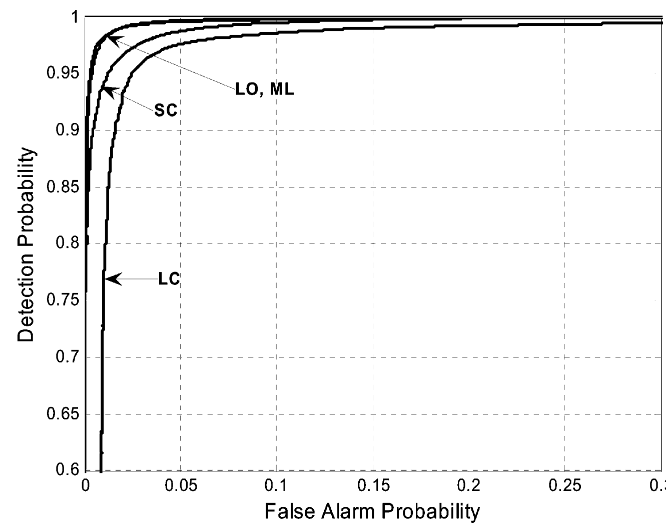


Fig. 6. Detection curves for ML, LO, SC, and LC detectors at SNR of 15 dB.

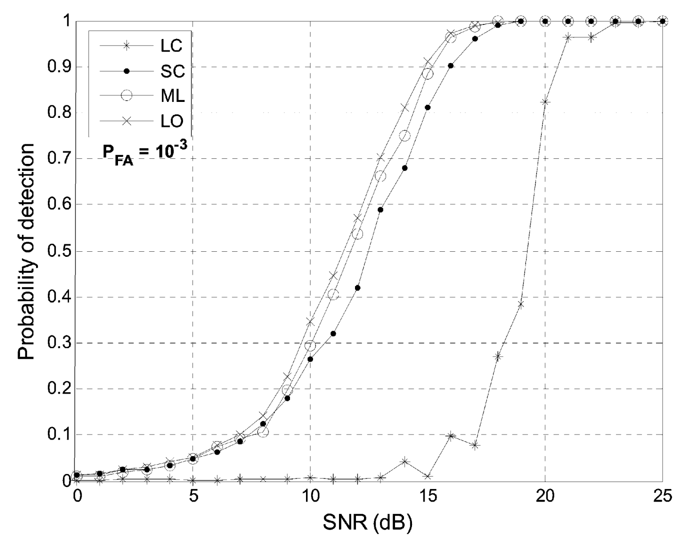


Fig. 7. Performance of a detector based on ML, LO, SC, and LC.

than the SC. However, it is more common to operate the detector at low values of $P_{\rm FA}$.

Fig. 5 shows the detection curves at a moderate SNR of 10 dB. The same trend is clearly visible; the ML and LO detectors are the best, followed by the SC, and then the LC. The LC again cannot achieve as low a $P_{\rm FA}$ as the others. At high values of detection probability and consequently $P_{\rm FA}$, the LC performance is somewhat worse than the other detectors. At intermediate values of $P_{\rm FA}$, the SC and LC performances are similar, but not as good as the ML and LO detectors.

At a high SNR of 15 dB, the SC performs only slightly worse than the ML and LO (Fig. 6). The LC is consistently inferior; it fails to achieve low $P_{\rm FA}$ and this trend continues at even higher SNRs.

Fig. 7 shows the performances of the detectors over a SNR range 0–30 dB for a probability of false alarm rate of 10^{-3} selected by choosing a detection threshold empirically. Although the detection curves suggest that the ML and LO detectors are significantly better than the SC detector, the low $P_{\rm FA}$ performance of the SC detector is only slightly inferior to the ML and LO detectors. The LC detector is considerably poorer, with a requirement of about 5–10 dB higher SNR for the same detection level.

The near-optimal performance and low complexity of the SC detector at low SNR makes it attractive for use as a detector in snapping-shrimp dominated ambient noise. When performance requirements are critical and the noise probability distribution parameters are known, an ML or LO detector may be used. The LO detector is simpler to implement and computationally less intensive than the ML detector. However, the latter has the advantage that it also provides an estimate of the signal amplitude, which the LO and SC detectors cannot do.

B. Experimental Validation

Although the simulations used ambient noise data recordings from the sea, actual mixing of the noise with the signal was performed numerically. The tests suggested that the SC detector should have a superior performance to the LC detector for data recorded in Singapore waters. To test whether this is indeed true, we tested both detectors with field data. The ML and LO detectors were not tested due to computational limitations and the unavailability of independent ambient noise samples to obtain detailed noise statistics.

A spread-spectrum signal with center frequency 40 kHz, spread 40 kHz and duration 30 ms was transmitted and recorded over a distance of 550 m in Singapore waters. Fig. 8 shows the experimental setup. The signal was repeated 100 times at a repetition rate of 10 transmissions per second. The signal was acquired at a sampling rate of 250 kSa/s and stored for later analysis.

Before detection, the received signal was prewhitened and bandpass filtered to reduce out-of-band noise. The filtered signal was then passed through LC and SC detectors with a threshold chosen to satisfy a $P_{\rm FA}$ of 10^{-6}. For this false alarm rate and a 10-s data set sampled at 250 kSa/s, one would expect 2.5 false alarms. Of the 100 transmissions, the LC detector correctly

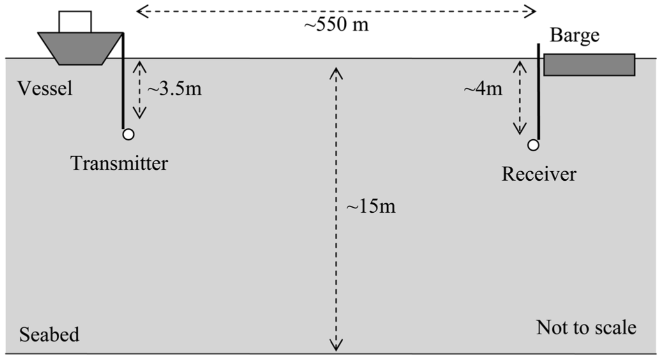


Fig. 8. Schematic representation of the experimental setup during sea trials.

identified 40 transmissions with three false alarms. The SC detector correctly identified 59 transmissions with one false alarm. The performance of the SC was clearly better than the LC in terms of detection probability and number of false alarms.

VI. Conclusion

We have demonstrated that snapping shrimp dominated ambient noise can be represented accurately by the $S\alpha S$ probability distribution. The parameters of the $S\alpha S$ distribution can be determined using fractile-based estimators. The knowledge of the noise probability distribution enables us to develop optimal ML and LO detectors. The performance of these detectors was found to be significantly better than the more conventional LC detector. For weak signals, a lower SNR could produce the same detection performance if an optimal detector was used instead of an LC detector. When the noise distribution parameters are unknown, a nonparametric SC detector may be used. The performance of this detector was found to be comparable but slightly inferior to the optimal detectors. The simple implementation and near-optimal performance of the SC detector make it an attractive choice for many applications.

The SC has subsequently been successfully used in several experiments [19]. On certain occasions, we have used the SC and ML detectors cooperatively. The SC detector was used with a high false alarm rate to identify potential detections. The potential detections were then passed through the ML detector for a more accurate detection and estimation of signal strength. As the SC detector is computationally faster, it was used to screen the data before the computationally complex ML estimator was invoked.

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