Robust passive diver detection in shallow ocean

Vishnu N. Hari, Mandar Chitre, Yuen Min Too, Venugopalan Pallayil
Acoustic Research Laboratory
National University of Singapore, Singapore

***Abstract*—This paper discusses the problem of passive detection of divers in a shallow water environment. The sound produced due to breathing of the open-circuit divers is prominent in the high frequency range of the data. We formulate a detector to detect the waveforms of a diver's breaths, which occur as periodic bursts of sound. This detector is robust to the presence of other interfering sources. Since the high-frequency noise spectrum in shallow waters is generally dominated by impulsive noise due to biological sources, we robustify the detector against the presence of these impulses to obtain improved detection performance. We demonstrate the effectiveness of these techniques using real data recorded from shallow waters around Singapore.**

Keywords*—*diver, detection, passive, robust.

I. Introduction

Detection of divers in coastal waters is an area of considerable importance for defense, security and general monitoring applications [1]–[3]. Diver detection systems usually employ active sonar to achieve good resolution and detection range. However, active sonars face challenges in coastal waters due to reverberation, and may also be limited by regulations on the sound level that can be produced by their pingers [1], [4]. Thus, passive diver detection is being pursued as an alternative [1], [4]–[6]. Passive systems are less power-hungry as compared to active systems since they do not have to use pingers. They are also more covert in monitoring as compared to active systems.

Passive systems have been found to be effective in the case of open-circuit divers. Thus, they are useful for applications involving monitoring of open-circuit divers such as recreational, commercial, scientific, safety and sports divers. Passive detectors attempt to detect the sound produced by divers that arises from turbulent air flow pressure fluctuation during breathing [7]. The bubbles caused due to exhalation are also a source of sound which can be detected. The primary limitation faced by passive systems in shallow waters is the high ambient noise level encountered. Moreover, the noise encountered in such waters is often impulsive in nature due to contribution from biological sources such as snapping shrimp, atmospheric activity and man-made sources [8]–[10].

In this paper, we focus on passive acoustic detection of open-circuit divers. Previously, Stolkin et al proposed a method for the detection of divers by observing the breathing rate modulation of the sound produced by them. We refer to this as a breathing rate detector (BRD) [11]. This detector makes use of the periodicity of the envelope of the diver's breathing which is prominently observable in the high frequency ranges. Later, Johansson et al modified this detector to make it robust to transient sources [12]. While effective, these methods have some shortcomings, such as requirement of long observation windows and sensitivity to impulses and interferers.

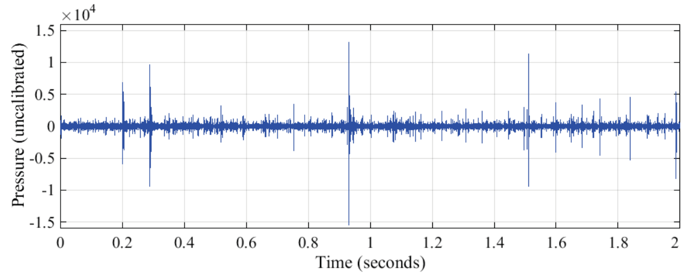

Fig. 1. Two-second sample timeseries from ROMANIS data.

We develop a diver detection algorithm which is based on a breathing waveform detector (BWD). This method overcomes some of the shortcomings of the existing methods and yields fairly good performance in a shallow water environment in the presence of interferers. In some cases when the noise is highly impulsive, the performance of the BWD may suffer. For such environments, we present a more robust version of the BWD referred to as robust BWD (RBWD), which yields better performance than the regular BWD in the presence of strongly impulsive noise. Robustness is infused into the robust BWD through the use of zero-order statistics [13]. We show that these algorithms are effective for practical diver detection systems using real data. This data was recorded using a hydrophone array deployed by Acoustic Research Laboratory (ARL) in shallow waters around Singapore.

The paper is organized as follows. In section II, we discuss the experiments done at ARL to test diver detection. In section III, we present the existing methods, and the breathing waveform detector and robust breathing waveform detector for diver detection. The performance of these methods will be compared and elaborated in section IV using real data collected from Singapore waters. Finally, in section V we conclude the paper.

II. Data collection

The ambient noise level in the shallow tropical waters such as those found around Singapore is high, and often impulsive due to natural and biological sources such as snapping shrimp [9]. Apart from this, man-made sources such as machinery and ships also act as interferers, impeding the performance of detectors. Dealing effectively with such a noise environment is essential to developing practical monitoring systems in such regions. In order to test the performance of passive diver detection in such an environment, we collected data from Singapore waters using a 508-element array called 'Remotely Operated Mobile Ambient Noise Imaging System' (ROMANIS) developed at ARL [14]. ROMANIS is a 2-D planar array with a diameter of 1.3 m and an operating frequency range of

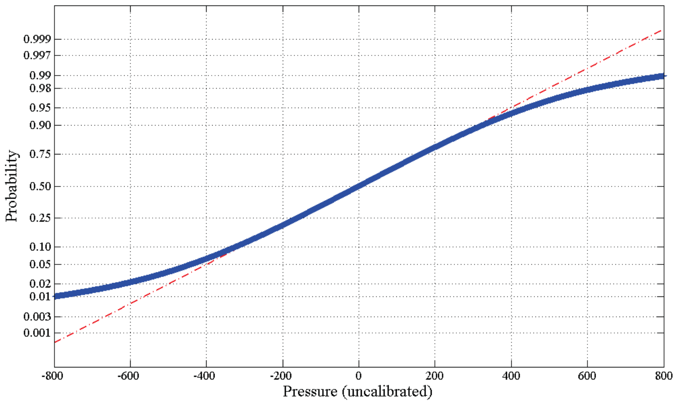

Fig. 2. Normal probability plot of ROMANIS data.

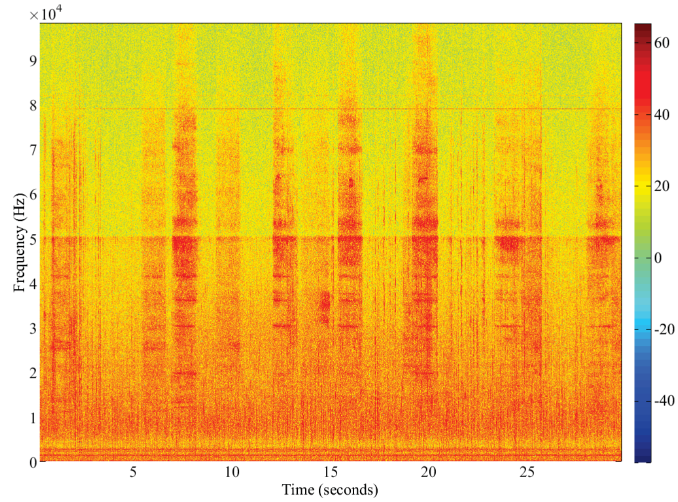

Fig. 3. Spectrogram of a 30-second spatially filtered recording of diver breathing.

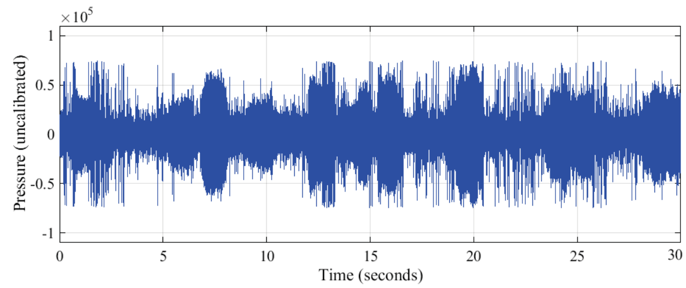

Fig. 4. A 30-second spatially filtered recording from ROMANIS data showing diver breathing.

25-75 kHz. Its elements have a sampling rate of $f_s = 196$ kSa/s. The array was deployed in 2010 near Selat Pauh island, Singapore for experiments.

A 2-second sample of the pressure timeseries data from the ROMANIS dataset which is bandpass-filtered within the band 25-75 kHz, is plotted in Fig. 1. The spikes evident in the dataset arise due to snaps from snapping shrimp, which often dominate the high-frequency noise in this region, and lead to the probability density function (pdf) of the noise becoming more heavy-tailed. Fig. 2 shows a normal probability plot of the noise data recorded from ROMANIS bandpass-filtered within $25 - 75$ kHz. We see that the dataset (solid blue line) has a heavy-tailed distribution due to the outliers.

In order to study the characteristics of the sound from a diver's breathing, we observe a set of recordings obtained using ROMANIS when a pair of open-circuit divers was present in the water. A 30-second timeseries was obtained by spatially filtering the recordings from 498 sensors of ROMANIS by steering it in the direction of the divers. The data from the remaining 10 sensors of ROMANIS was not used because the sensors were faulty. In Fig. 3 we plot the spectrogram of the spatially filtered data against frequency and time, which is computed using 8192 fast Fourier transform (FFT) points with 50% overlap between successive windows.

In Fig. 3, the frequency signature of the two divers' breathing can be observed as the occasional broadband bursts of energy that occur in the spectrum. It is clear that the divers' breathing signature is most evident against the background noise in the high-frequency range. The same has been reported earlier by other authors [11], [12]. The 25-75 kHz frequency band will be utilized for the detection of the diver. There is no visible difference in the frequency characteristics of breathing from each diver, because the frequency characteristics depend more on the breathing apparatus used than the characteristics of the diver [15]. The high-frequency contribution to the breathing signature arises from the turbulent decompression of the gas during breathing [5]. The timeseries of the 30-second spatially filtered recording, bandpass-filtered within 25-75 kHz, is shown in Fig. 4. The exhalation of the divers can be observed as sustained bursts in the timeseries that last about 1 to 1.3 seconds.

III. Detection Methods

In this section, we discuss some of the existing methods for passive acoustic detection of divers, and then propose two new methods called BWD and RBWD for detection. Our study is limited to cases where a maximum of two divers are present in any single direction, and we assume that the envelopes of their breathing do not have a significant overlap in time. In the discussions that follow, we will use small boldface letters to denote vectors representing timeseries, and small italic letters to denote each time sample of the vector. A vector $\mathbf{x}$ of N samples is expressed as

$$\mathbf{x} = [x(1), x(2)...x(N)]^T, \tag{1}$$

where ^{T} denotes transpose. We also define $\mathbf{x}^2$ as the vector whose samples are the squares of samples of $\mathbf{x}$.

We consider a diver detection system which scans over the azimuthal directions of interest using a spatial beamformer. We steer the hydrophone array towards an azimuth θ, and obtain the N-sample pressure timeseries vector which is bandpass-filtered within the frequency band of interest. This timeseries is denoted by the column vector $\mathbf{y}_\theta$. We then compute the data vector $\mathbf{z}_\theta = [z_\theta(1), z_\theta(2)...z_\theta(N)]^T$, whose samples are the magnitudes of the samples of $\mathbf{y}_\theta$.

A. Previous methods

Stokin et al [11] presented a method to detect divers by detecting their breathing rate, which was later experimentally tested by Lennartsson et al [16]. The envelope of the breathing signature of a human diver appears at a breathing rate which lies within the band 0.15-0.4 Hz, called the 'diver frequency band'. Detection is done by performing an FFT on $\mathbf{z}_\theta$, the envelope of the divers' breathing. The energy in the diver frequency range is integrated and used as the test statistic to detect a diver's presence. When searching for the presence of two divers, the search range should extend to a higher frequency of about 0.7 Hz. We refer to this method as the breathing rate detector (BRD). Later, Johansson et al [12] attempted to modify the BRD to make it robust to impulses. This was done by using a test statistic consisting of the product of the test statistic of the BRD with the ratio of the power in the diver frequency range and that in a frequency range higher than the diver frequency. We refer to this as the robust breathing rate detector (RBRD).

However, these methods suffer from certain drawbacks. They are sensitive to impulses, because the presence of an impulse manifests as a burst of power across all frequencies of the spectrum. This leads to an increase in the test statistic of the detectors irrespective of whether a source was present or not, which leads to false alarms. This is especially true in the case of the BRD. The RBRD is designed to avoid these false alarms, but it is still sensitive to impulses. Since both these methods search for very low breathing rates, they require a large observation window to be able to obtain good detection, and their performance falls with reduction in observation length. These methods are also sensitive to the presence of other non-impulsive interferers in the environment.

B. Breathing waveform detector

We formulate a breathing waveform detector that can overcome some of the drawbacks of the existing methods. The detector is formulated based the observation that the envelope of a diver's breathing extends for a certain duration. We determined this duration to be 1.2 seconds per breath on an average. Hence, the aim here is to detect the breathing waveform as bursts of sound that sustain for a duration Δ samples (where $\Delta \approx 1.2 f_s$), against the background noise.

We define an $N \times 1$ vector $\mathbf{r}(n_0, \Delta)$ as a rectangular pulse that denotes the envelope of a single breath that starts at the n_0^{th} sample and lasts Δ samples. The n^{th} sample of this vector is given by

$$r(n) = U(n - n_0) - U(n - n_0 - \Delta), \tag{2}$$

where $U(.)$ denotes the unit step function. Consider that there are B diver breaths present in a given N-sample data vector, each starting at the sample numbers n_1, n_2... n_B. Then, the $N \times 1$ breath envelope vector $\mathbf{s}$, which is the sum of the envelopes of all the breaths in a given data vector, is given by

$$\mathbf{s} = \sum_{i=1}^{B} \mathbf{r}(n_i, \Delta). \tag{3}$$

The problem of detecting the diver can now be formulated as one of detecting the breath envelope vector $\mathbf{s}$ with unknown amplitude A in a given data vector, in the presence of noise. Since we do not know the starting samples $n_1, n_2, ...n_B$ of the B possible breaths, these should be replaced by their maximum likelihood estimates (MLEs) $\hat{n_1}$, $\hat{n_2}$...$\hat{n_B}$. Then we can express the MLE of $\mathbf{s}$ as

$$\hat{\mathbf{s}} = \sum_{i=1}^{B} \mathbf{r}(\hat{n_i}, \Delta). \tag{4}$$

In a conventional approach which does not take into account the impulsive nature of the ambient noise, one would assume that the samples of $\mathbf{y}_\theta$ are independent and identically distributed (i.i.d) random variables following a Gaussian pdf. This would mean that the samples of $\mathbf{z}_\theta$ follow a Rician pdf. Then, in the presence of the divers, the joint pdf of the samples of $\mathbf{z}_\theta$ parameterized by a scale parameter σ, is given by

$$p(\mathbf{z}_\theta) = \frac{\prod_{i=1}^{N} z_\theta(i) I_0\left(\frac{A z_\theta(i) s(i)}{\sigma^2}\right)}{\sigma^{2N}} \times \exp\left(-\frac{\sum_{i=1}^{N}\left(z_\theta^2(i) + A^2 s(i)\right)}{2\sigma^2}\right), \tag{5}$$

where $I_0(.)$ is the modified bessel function of the first kind with order zero. Based on binary hypothesis testing, we can derive the generalized likelihood ratio detection test statistic to test the 'signal-present hypothesis' H_1 ($A > 0$) against the 'signal-absent hypothesis' H_0 ($A = 0$). The test statistic $T(\theta)$ as a function of the looking direction θ is obtained as

$$T(\theta) = \log\left(\frac{M(\mathbf{z}_\theta^2)}{2\hat{\sigma}_1^2}\right) - \frac{0.5B\hat{A}^2}{N} - \frac{M\left(\mathbf{z}_\theta^2\right)}{2\hat{\sigma}_1^2} + \frac{B}{N} M\left(\log\left(I_0\left(\frac{A\mathbf{a}_\theta}{2\hat{\sigma}_1^2}\right)\right)\right), \tag{6}$$

where $M(.)$ is the arithmetic mean of a vector. The arithmetic mean of an N-sample vector $\mathbf{x}$ is given by

$$M(\mathbf{x}) = \frac{1}{N}\sum_{1}^{N} x(i). \tag{7}$$

The term $\mathbf{a}_\theta$ is the $B\Delta \times 1$ vector of data samples in $\mathbf{z}_\theta$ that lie within the estimated breath envelope $\hat{\mathbf{s}}$. $\mathbf{a}_\theta$ is given by

$$\mathbf{a}_\theta = \left[\mathbf{b}_\theta^T(\hat{n_1}), \mathbf{b}_\theta^T(\hat{n_2}), ..., \mathbf{b}_\theta^T(\hat{n_B})\right]^T, \tag{8}$$

where $\mathbf{b}_\theta(n_i)$ refers to the $\Delta \times 1$ vector of the n_i^{th} to $n_i + \Delta^{th}$ data samples, and is given by

$$\mathbf{b}_\theta(n_i) = \left[z_\theta(n_i), z_\theta(n_i + 1), ..., z_\theta(n_i + \Delta - 1)\right]^T. \tag{9}$$

The term $\hat{A}$ is the MLE of A, and $\hat{\sigma_1^2}$ is the MLE of σ^2 under the hypotheses H_1. Obtaining $\hat{A}$ and $\hat{\sigma}_1^2$ jointly by maximum likelihood is a computationally complex process. However, they can easily be estimated sub-optimally as

$$\hat{\sigma}_1^2 = \frac{0.5}{N - B}\left(NM(\mathbf{z}_\theta^2) - BM(\mathbf{a}_\theta^2)\right) \tag{10}$$

$$\hat{A} = M(\mathbf{z}_\theta^2) - 2\hat{\sigma}_1^2 \tag{11}$$

It can be shown that the MLE of $\mathbf{s}$ is that which maximizes the test statistic $T(\theta)$ for the given $\mathbf{z}_\theta$. Hence, we can obtain a set of sub-optimal estimates of n_i's in a sequential manner as follows. In each step of the sequential estimate, we select the $\hat{n_i}$ that yields maximum improvement in $T(\theta)$ such that it does not overlap with any previous windows $\mathbf{b}_\theta(\hat{n_1}), ...\mathbf{b}_\theta(\hat{n_{i-1}})$. Based on this, the vector $\mathbf{a}_\theta$ is updated by appending $\mathbf{b}_\theta(\hat{n_i})$ to it, and the test statistic is also updated. We repeat this until no more improvement can be obtained in the value of $T(\theta)$ or no more breath envelopes can be fit to the given data without overlap. The maximum test statistic obtained is used as the final test statistic.

We refer to the detector employing the test statistic in (6) as the BWD.

C. Robust breathing waveform detector

Recall that the BWD is formulated for the case when the elements of the data vector $\mathbf{y}_\theta$ follow a Gaussian pdf. However, as seen in section II, the recorded sensor array data is contaminated by impulses which cause the pdf of the beamformer output to become highly non-Gaussian. Hence the BWD is sensitive to impulsive noise and unfit for detection in cases when the impulsiveness is severe. We address this sensitivity by adapting the detector to be robust in impulsive noise.

Note that the term $M(\mathbf{z}_\theta^2) = \frac{1}{N}\sum_{i=1}^{N} y_\theta^2(t)$ in equation (6) is the second order estimate of the power of $\mathbf{y}_\theta$. Likewise, the term $M(\mathbf{a}_\theta^2)$ is the second order estimate of the power of the samples of $\mathbf{y}_\theta$ that lie within the estimated breath envelope. However, in the presence of strongly impulsive noise, the second order power estimator may break down. Hence we introduce robustness into the BWD by using a geometric mean estimator $G(.)$ in the test statistic instead of $M(.)$. The geometric mean of a vector $\mathbf{x}$ is defined as

$$G(\mathbf{x}) = \left(\prod_{1}^{N} x(i)\right)^{1/N} \tag{12}$$

The geometric mean is effectively a zeroth order estimator of the power, and yields more robustness to the effect of impulses [13]. We refer to the detector that uses a test statistic obtained by replacing $M(.)$ with $G(.)$ in (6), (10) and (11), as the robust breathing waveform detector (RBWD).

IV. Results

In this section, we present some results to compare the effectiveness of the diver detection methods discussed, namely the BRD, RBRD, BWD and RBWD, using data collected from shallow waters around Singapore. Using a subset of 26 sensors of ROMANIS which are located on a horizontal line, we perform a 1-D search over the azimuth angles from $-18°$ to $18°$ in steps of $0.5°$ to obtain the timeseries corresponding to each looking angle. The detection test statistics are then computed for each looking angle using the methods discussed in section III.

We first demonstrate the performance of the methods by comparing their output test statistics for two datasets. First, we consider a 10-second dataset named #1, which was collected

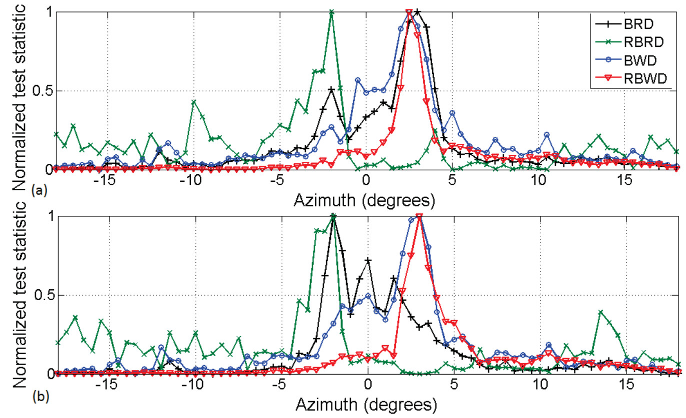

Fig. 5. Normalized test statistics comparing the detection methods with dataset #1.

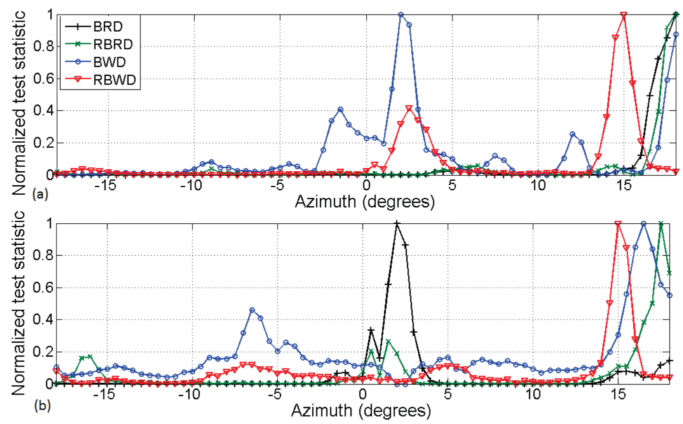

Fig. 6. Normalized test statistics comparing the detection methods with dataset #2.

on April 10^{th}. During the recording of #1, two divers were present at an azimuth of $3.5°$ with respect to the array. Apart from the background noise, a loud interferer was also present at an azimuth of $-2.5°$ throughout the recording. Fig. 5 compares the test statistics of detectors using (a) the first 5 seconds of the data, and (b) using the last 5 seconds of the data. For fair comparison, the test statistics are normalized in such a way that their noise floor and peaks fall within the range 0 to 1.

In Fig. 5, we see that both the BWD and RBWD are able to successfully detect the divers present at $3.5°$ in both cases (a) and (b). Their performance is more or less similar for dataset #1. However, the BRD fails to detect the divers in case (b), and the RBRD fails to detect the divers in both cases (a) and (b). This is due to the effect of the interferer present at $-2.5°$.

We now consider another 10-second dataset named #2 contaminated by impulsive noise, which was collected on April 11^{th}. During the experiment, two divers were present at an azimuth of $15°$ with respect to the array. Fig. 6 compares the normalized test statistics of the detectors using (a) the first 5 seconds of the data, and (b) using the last 5 seconds of the data.

In Fig. 6, we see that the BRD, RBRD and BWD fail to detect the diver in dataset #2, in both cases (a) and (b). This is due to the arrival of strong impulses from $0°$ and $18°$, which

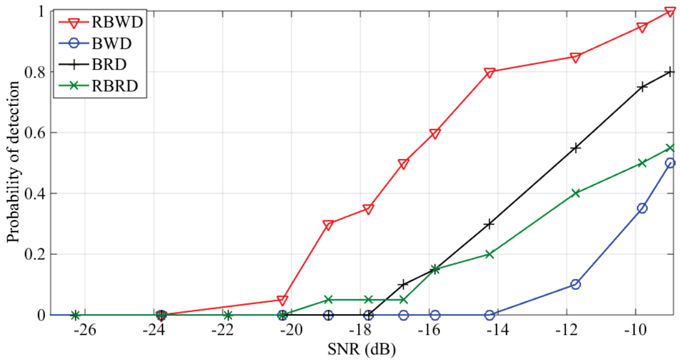

Fig. 7. Variation of probability of detection with the SNR (in dB), using a combination of datasets #3 and #4. The false alarm probability for this plot is 0.05.

affect the performance of these detectors. On the other hand, the RBWD is robust to the presence of these impulses, and is able to robustly detect the divers in both the cases.

Now, we compare the performance of the detectors in terms of the variation of their probability of detection (P_D) with the signal strength. For this, we utilize two datasets - a 'signal' dataset #3, which contains a high signal-to-noise ratio (SNR) recording of the divers' breathing with relatively less noise, and a 'noise' dataset #4, which consists of only ambient noise which is highly impulsive. Datasets #3 and #4 are combined in different ratios to obtain data with different SNRs. Output test statistics computed using multiple windows from the data constitute separate trials. A peak in the test statistic in the direction of the diver is treated as a detection, and a peak anywhere else in the searched azimuth space is a false alarm. In Fig. 7, we plot the variation of P_D at a probability of false alarm of 0.05, with the variation in the SNR of the beamformer output.

In Fig. 7, we see that the RBWD outperforms all the other detectors in terms of detection performance. Using the RBWD yields about 4 dB of improvement over the BRD and 5.4 dB over the RBRD. In the current dataset, the performance of the BWD breaks down due to the presence of impulses in the data, and it shows a performance worse than the BRD and RBRD as well. However, the RBWD is able to effectively negate the effect of these impulses and detect the divers. The use of the geometric mean estimator in the RBWD lends it an SNR improvement of about 8 dB over the BWD.

V. Conclusion

We have elaborated robust and effective methods for passive acoustic diver detection in shallow waters. We tested these methods with data recorded from Singapore waters and compared them against existing methods from the literature. The technique proposed by us is to detect divers by searching for their breathing waveform in the observed acoustic data. The breathing waveform detector proposed by us is robust against non-impulsive interferers, but its performance suffers in highly impulsive noise. The robust breathing waveform detector presented by us showed good performance even in the presence of impulsive noise. This method showed consistently better performance than the existing breathing rate detection techniques.

With the development of these algorithms, we take the capability of passive diver detection systems another step ahead. In the future, with sufficient improvement, passive detection systems could become favorable for use for detecting open-circuit divers as compared to active systems in scenarios where there are limitations on the noise generated by the latter. To extend our work, it would be interesting to consider the tracking of moving divers, and aspects of implementation of these algorithms in an efficient manner. It would also be exciting to take up passive detection of closed-circuit divers, such as that done in [5], which is a more challenging problem as compared to open-circuit divers.

References

[1] R. Lennartsson, E. Dalberg, A. Johansson, L. Persson, S. Petrovic, and E. Rabe, "Fused passive acoustic and electric detection of divers," in *International WaterSide Security Conference*. Carrara: IEEE, Nov. 2010, pp. 1–8.

[2] A. Crawford, A. Percival, and V. Crowe, "Use of small imaging sonars for diver identification," in *IEEE International Conference on Technologies for Homeland Security (HST)*. Waltham: IEEE, Nov. 2011, pp. 262–266.

[3] (2014, Sep.) Dsit discloses the israeli navy as one of its customers. [Online]. Available: http://www.dsit.co.il/sitefiles/1/114/12478.asp

[4] L. Fillinger, M. Chitre, and V. Pallayil, "Passive diver detection in warm waters," in *1st International Conference and Exhibition on Underwater Acoustics*, Corfu, 2013, pp. 1459–1464.

[5] L. Fillinger, A. Hunter, M. Zampolli, and M. Clarijs, "Passive acoustic detection of closed-circuit underwater breathing apparatus in an operational port environment," *The Journal of the Acoustical Society of America*, vol. 132, no. 4, pp. 310–316, Oct. 2012.

[6] L. Fillinger, A. Hunter, and M. Clarijs, "Passive sonar denoising for diver detection in presence of snapping shrimp," in *2nd International Conference and Exhibition on Underwater Acoustics*, Rhodes island, 2014, pp. 825–830.

[7] D. Donskoy, N. Sedunov, A. Sedunov, and M. Tsionskiy, "Variability of SCUBA diver's acoustic emission," in *SPIE 6945, Optics and Photonics in Global Homeland Security IV*, C. S. Halvorson, D. Lehrfeld, and T. T. Saito, Eds., Orlando, Apr. 2008, pp. 1–11.

[8] D. Bertilone and D. Killeen, "Statistics of biological noise and performance of generalized energy detectors for passive detection," *IEEE Journal of Oceanic Engineering*, vol. 26, no. 2, pp. 285–294, Apr. 2001.

[9] M. Chitre, J. Potter, and S. Ong, "Optimal and Near-Optimal Signal Detection in Snapping Shrimp Dominated Ambient Noise," *IEEE Journal of Oceanic Engineering*, vol. 31, no. 2, pp. 497–503, Apr. 2006.

[10] F. Machell, C. Penrod, and G. Ellis, "Statistical characteristics of ocean acoustic noise processes," in *Topics in Non-Gaussian Signal Processing*, E. J. Wegman, S. C. Schwartz, and J. Thomas, Eds. New York: Springer New York, 1989, pp. 29–57.

[11] R. Stolkin, A. Sutin, S. Radhakrishnan, M. Bruno, B. Fullerton, A. Ekimov, and M. Raftery, "Feature based passive acoustic detection of underwater threats," in *Proc. SPIE*, vol. 6204, Orlando, 2006, pp. 620 408–620 408–10.

[12] A. Johansson, R. Lennartsson, E. Nolander, and S. Petrović, "Improved passive acoustic detection of divers in harbor environments using prewhitening," in *Proc. OCEANS 2010*, Seattle, 2010.

[13] J. Gonzalez, J. Paredes, and G. Arce, "Zero-order statistics: A mathematical framework for the processing and characterization of very impulsive signals," *IEEE Transactions on Signal Processing*, vol. 54, no. 10, pp. 3839–3851, 2006.

[14] M. Chitre, S. Kuselan, and V. Pallayil, "Ambient noise imaging in warm shallow waters; robust statistical algorithms and range estimation," *The Journal of the Acoustical Society of America*, vol. 132, no. 2, pp. 838–47, Aug. 2012.

[15] K. Chung, H. Li, and A. Sutin, "A Frequency-Domain Multi-Band Matched-Filter Approach to Passive Diver Detection," in *Proc. Forty-First Asilomar Conference on Signals, Systems and Computers*. Pacific Grove: IEEE, Nov. 2007, pp. 1252–1256.

[16] R. Lennartsson, E. Dalberg, L. Persson, and S. Petrovic, "Passive acoustic detection and classification of divers in harbor environments," in *Proc. OCEANS 2009*, Biloxi, 2009.