

Separation and Classification of Underwater Acoustic Sources

Mehdi Rahmati, Parul Pandey, and Dario Pompili

Dept. of Electrical and Computer Engineering, Rutgers University–New Brunswick, NJ

e-mail: {mehdi_rahmati, parul_pandey, pompili}@cac.rutgers.edu

Abstract—Advancements in oceanic research have resulted in a plethora of activities such as undersea oil/gas exploration, environmental monitoring, SONAR-based coastal surveillance, which all have increased the acoustic noise levels in the ocean, raising concerns in the scientific community. Knowledge about the statistical characteristics of noise sources and their spatial distribution is important for understanding the impact on marine life as well as for regulating and policing such activities. Furthermore, as studies have shown, assuming the underwater noise to be Gaussian is seldom valid; hence, *online profiling* of the sources forming the ambient noise is also essential to increase the performance of acoustic communication systems in the harsh underwater environment. In this paper, *real-time separation* of underwater acoustic noise sources via Blind Source Separation (BSS) in the presence of various degrees of multipath as well as their *classification* based on the coherence of their Power Spectral Density (PSD) and the PSD of known noise sources are studied via simulations. Work is currently being conducted to validate the results and to localize the sources using real data collected from underwater communication testbeds.

I. INTRODUCTION

Underwater communications and sensor networks enable a variety of applications such as undersea oil/gas exploration, environmental monitoring, and coastal surveillance to name just a few [1]. All these activities contribute significantly to the underwater acoustic noise: e.g., *shipping noise* is generated from cargo-vessel engines, *drilling/extraction noise* is produced by airgun arrays used to detect oil/natural gas beneath the seafloor, *SONAR noise* is generated from military systems to detect submarines (Fig. 1). These noise sources are often high power and occupy the same frequency band as those used by marine animals (Fig. 2), which makes it hard for the animals to communicate and distinguish human-generated noise from natural sounds leading to accidental collisions and mass beachings. Other impacts include causing animals to alter their behavior, preventing them from hearing important sounds (masking), causing hearing loss (temporary or permanent), or damaging tissue. In at least a few well-documented cases there is a relationship between the use of mid-frequency SONAR and the stranding of cetaceans, particularly beaked whales [2]. As a result, there are raising concerns in the scientific community about the effect of human-generated sounds on marine life, which has become a topic of increasing controversy, especially regarding marine mammals.

Knowledge about the *statistical characteristics* of these noise sources and their *spatial distribution* is important for better understanding their impact on marine life as well as for regulating and policing shipping and undersea activities

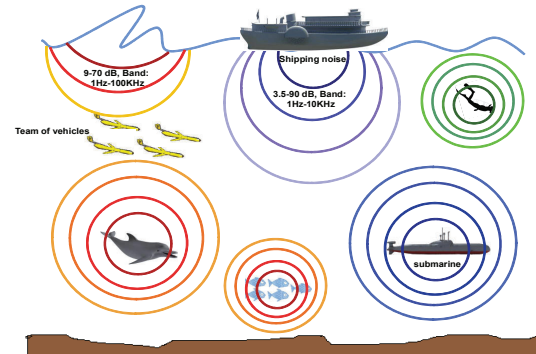


Fig. 1: Example of underwater dominant acoustic noises.

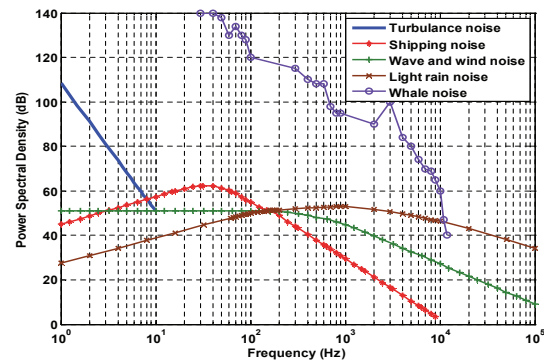


Fig. 2: Power Spectral Density (PSD) [dB re μ Pascal] of sample acoustic noise sources, as reported in [3], [4].

– both civilian and military. Furthermore, *online profiling* (e.g., *separation*, *classification*, *statistical analysis*) of the dominant sources forming the ambient noise is also essential to increase the performance of acoustic communication systems in the harsh underwater environment. Typically, in the presence of noise and interference, signal-detection performance of communication systems degrades [5]. The problem becomes more severe and complex to compensate for when the noise distribution is not known. Data-driven studies have shown that the assumption of noise to be additive Gaussian is seldom valid in ocean environments [6]–[8]. In this unfavorable condition, the received signal is mixed with the ambient noise with an unknown distribution, leading to poor performance when traditional reception techniques assuming additive Gaussian noise are adopted.

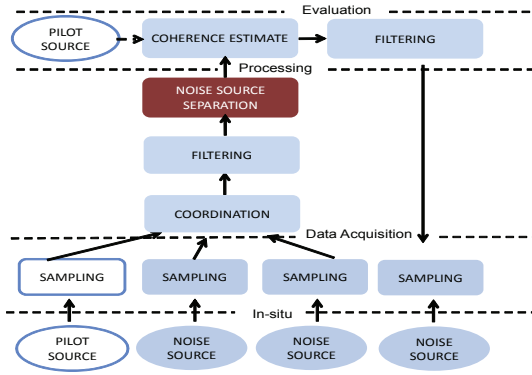


Fig. 3: Task workflow to achieve noise source separation.

The time-varying underwater acoustic channel offers unique challenges in the classification (and localization) of noise sources in the presence of varying degrees of multipath [9], [10], whose formation is caused by two effects: (i) reflection at the surface, bottom and by any object, and (ii) refraction in the water (the latter being caused by the sound-speed variation due to salinity, temperature, and depth, which is mostly evident in deep-water channels). Online noise source detection is a challenging problem in this highly dynamic underwater environment.

To overcome these challenges, we propose to apply Blind Source Separation (BSS) [11] to separate on the fly noise sources in the presence of multipath. Since the number of dominant noise sources are unknown and because we have limited number of sensors/microphones, we design a filter with variable pass bandwidth that controls the input of the BSS algorithm. Through coordination, we iteratively change such bandwidth and estimate the similarity of the separated signals with a *pilot source* that we generate and inject into the system to find out the number of dominant noise sources in each sub-band. We also characterize the sources based on the *coherence* of their Power Spectral Density (PSD) and the PSD of known noise sources. Simulations show the effectiveness of the proposed solution under varying degrees of multipath.

The remainder of the paper is organized as follows: Sect. II focuses on the problem definition and describes our solution; Sect. III presents the current simulation results; finally, Sect. IV concludes the paper and gives insights into our future plan involving validating the simulation results and localizing the sources using real data collected from underwater communication testbeds.

II. PROBLEM DEFINITION AND PROPOSED SOLUTION

Because of the impact of man-made noise on marine life, it is essential to separate its dominant sources and determine their statistical characteristics. The output of the proposed online noise-analysis approach is useful towards the identification and classification of the sources, and can be used for various applications. Here, we explain how our approach works even in a heavy multipath environment and how networked

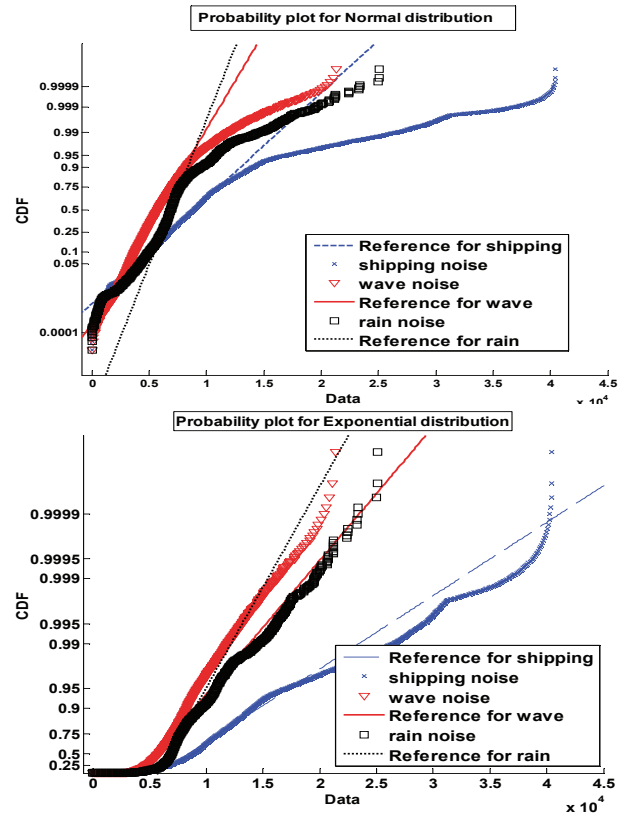


Fig. 4: Statistical deviation of noise sources from Normal distribution (top) and Exponential distribution (bottom).

nodes/receivers should coordinate to implement it.

Figure 3 depicts the *task workflow* to accomplish noise-source analysis, which spans three stages: (i) in-situ data acquisition, (ii) data processing (including “noise source separation”, in red), and (iii) online evaluation of the results for coordination purposes. Interestingly, Fig. 4 compares the Cumulative Density Function (CDF) of three noise sources (shipping, wave, and rain) against two known distributions, Normal (top) and Exponential (bottom), respectively, where the reference line represents the known distribution. These figures show that the three noise sources cannot be modeled using simplistic known distributions as their statistical deviations are not negligible. In the following, each stage is described.

(i) *Data acquisition*: It relies on the collaboration among different sensor nodes to collect the noise data from different locations. For a specific region of interest, in the initialization step a few nodes are selected to collect data. In each iteration of the algorithm, the estimation error is calculated so to tune the filter and bound the number of dominant noise sources in each sub-band; this way, BSS can detect the noise signals with an acceptable quality.

(ii) *Data processing*: In general, acoustic noise generated from seismic, shipping, drilling, and SONAR activities spans over a wide range of frequencies; however, each of these

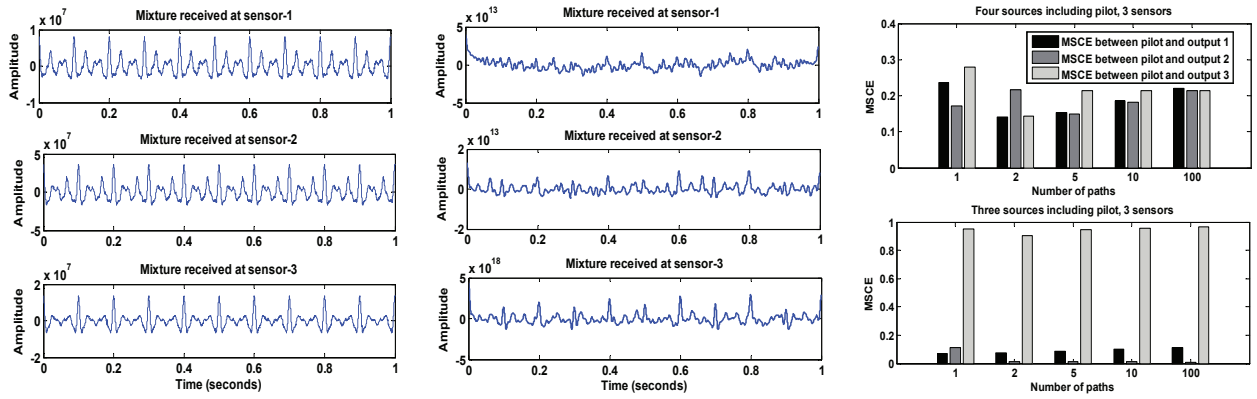


Fig. 5: Received noise at sensors with (a) $BW = \Delta f_1$ and (b) $BW = \Delta f_2$ when f_0 [Hz] is the central frequency and multipath has two paths ($N = 2$); (c) Coherence estimate for two filters $BW = \Delta f_1$ (wide, upper figure) and Δf_2 (narrow, lower figure).

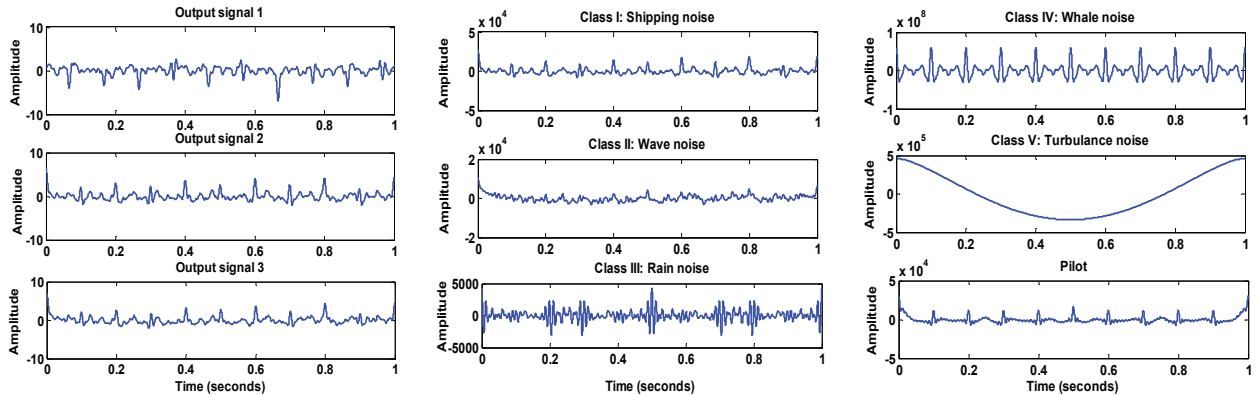


Fig. 6: (a) Separated outputs of Blind Source Separation (BSS); (b-c) Original classes of five source signals plus Pilot.

sources are dominant in specific bands. For example, seismic noise is dominant in the Extremely Low Frequency (ELF) band, i.e., below 1 Hz, while ocean turbulence is dominant in the Very Low Frequency (VLF) band, i.e., from 1 to 10 Hz; shipping noise dominates from 10 to mid-hundreds Hz, whereas wave and wind noise are dominant from mid-hundreds Hz to 50 kHz [3]; thermal noise is dominant after 50 kHz; and noise by marine mammals such as whales is dominant from 30 Hz to 10 kHz [4]. Consequently, we can first separate the noise sources in non-overlapping bands via a bank of bandpass filters; subsequently, we perform BSS on each band separately (e.g., in parallel).

(iii) *Estimation of noise sources*: The received signal at each node is a *mixture* of all noise sources; our goal is to separate each of the sources and estimate their statistical characteristics. We apply BSS [11] to separate the sources from their mixture and to estimate the (unknown) underwater channel coefficients (hence the name ‘blind’). If $S(t) = [s_1(t) \dots s_N(t)]^T$ represents the matrix of N ambient sources and $X(t) = [x_1(t) \dots x_M(t)]$ is the observation vector, formed by M mixtures (with $M \geq N$), we have $X = AS(t)$, which states that the observation is a linear

combination of sources where A represents the mixing matrix. Under the assumption that the noise sources are *statistically independent*, i.e., $E\{S(t)S(t)^H\}$ is *diagonal*, the goal of BSS is to find a separating matrix B to apply to the mixture so to estimate the sources as $Y(t) = BX(t)$, where $Y(t) = [y_1(t) \dots y_N(t)]$ is the matrix of the estimated sources.

Now, assume all ambient noise sources are bandwidth limited. For an injected pilot signal, the magnitude squared coherence estimation error $|Y(t) - S(t)|$ is calculated as in Algorithm 1. If the coherence error of the separated pilot signal and its original one (known) is below a pre-defined threshold, we conclude that BSS works well for the other noise sources too; otherwise, we re-tune the filter (by decreasing the width of the sub-bands) and repeat the test until we find the desired coherency for the pilot.

Afterward, in an offline phase, we compare the outputs of BSS with a pre-stored database and classify the noise sources. Note that BSS is computationally intensive as it involves eigen-vector calculations and matrix multiplications. Hence, individual nodes may not be able to produce meaningful results under realistic time constraints due to their insufficient computing capabilities. We leverage our work on distributed

Algorithm 1 Noise Source Separation

Input: Signal mixtures

Output: Separated signals

Initialization

Design a filter with non-overlapping sub-bands

while *Coherence estimate error* > *Threshold* **do**

Select a filter with a specific bandwidth

Inject the pilot source signal

Sample noise mixtures

Blind Source Separation

Calculate coherence estimate (MSCE) for pilot

Calculate error for the pilot signal

end while

Calculate the MSCE of the signals w.r.t. the database

 Classify the sources

computing to organizing and harness the capabilities of nodes in the neighborhood and form an *elastic resource pool* [12]. Moreover, this framework guarantees *autonomic* properties, namely, self-organization, self-optimization, and self-healing, which will enable formation of the elastic pool, task allocation, and protection against failure of nodes under resource and data uncertainty.

III. PERFORMANCE EVALUATION

We present here the simulation performance of our BSS-based noise separation algorithm assuming for simplicity that the ambient noise is constituted by $N = 3$ dominant noise sources, i.e., *shipping* (man-made noise), *whale* (marine animal sound), and *wave* (natural event), and that we avail *only* $M = 3$ mixtures (*worst scenario*), which are collected by static sensors deployed at three different locations (note that if we had more mixtures, performance would improve). One of the assumptions in BSS is that the number of signals in the mixtures is known apriori; in general, however, it is not possible to know all of the noise sources because of the wide diversity of sources in the oceanic environment. We assume here that we have a known pilot signal and also a filter with variable bandwidth and central frequency. Such pilot is used to estimate the number of *dominating* sources in each sub-band created by the filter.

While keeping the noise sources fixed, in our simulations we have considered three simultaneous received signals at each sensor in Fig. 5(a) in a wide filter as $BW = \Delta f_1 = 1$ KHz and $f_0 = 500$ Hz for the received signals. After reducing the bandwidth of the filter as, for example, $BW = \Delta f_2 = 100$ Hz and central frequency $f_0 = 50$ Hz the BSS output is shown in Fig. 5(b). Suppose we cast the problem in a specific environment, for example a 2-path environment with specific distances, in which there are three dominant sources plus our pilot: Fig. 5(c) compares the result of coherence estimation for both filters. As illustrated in this figure, the output of BSS for pilot signal in the narrower filter Δf_2 has a better coherence estimate and we can conclude that the number of sources matches the number of sensors; thus, if we neglect the pilot signal, we have two more sources that can be seen at the output of BSS and will be classified w.r.t. a database in an

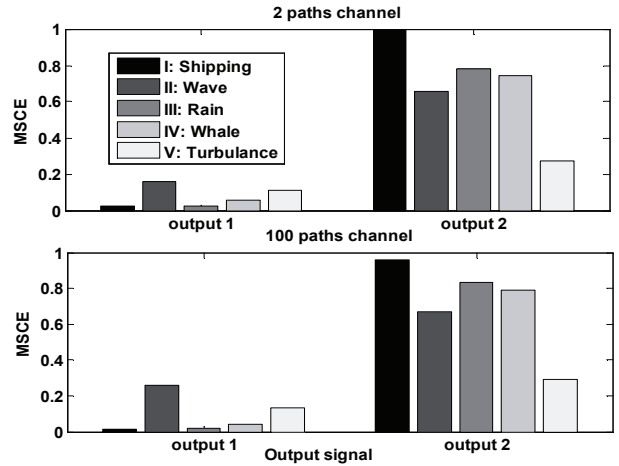


Fig. 7: Comparison of the coherence of the output of BSS against known noise sources for light and heavy multipath.

offline phase. For the wider filter in Fig. 5(c) (upper figure), the coherence does not reach 30% in the best case, which is not an acceptable value; thus, BSS does not work properly in the wide filter Δf_1 assumed in Fig. 5(a). However, it shows a reasonable coherence for the narrower filter as depicted in Fig. 5(c) (lower figure).

Once we have separated the noise sources, the next goal is to characterize their type: we perform Fast Fourier Transform (FFT) of the estimated signals and estimate the coherence of their Power Spectral Density (PSD) with the PSD of known noise sources. The coherence is measured using the Magnitude Squared Coherence Estimate (MSCE), which is calculated using the Welch's averaged modified periodogram method [13]. The MSCE is a function of frequency with values ranging in $[0, 1]$ indicating how closely the original noise source corresponds to the estimated source at each frequency; hence, the coherence is a function of the PSD of the source and the estimated noise as well as of the cross PSD of the two. Figure 6(a) shows the output of BSS for the successful separation discussed in Fig. 5(c) for two multipath environments. In this case, regarding several known noise sources of Fig. 6(b-c), the classification process will be implemented. The results are illustrated in Fig. 7. We observe that output 1 belongs to wave class noise sources and the second output displays a noise in shipping class, respectively, considering the MSCE calculations. Figure 8 also compares the PSD of shipping noise, as the output of BSS, and the known typical shipping PSD.

In our simulations we have used the underwater channel pathloss model defined in [14], i.e., $A(l, f) = A_0 l^k a(f)^l$, where f is the frequency, l is the distance, A_0 is a scaling factor, and $a(f)$ is defined as $0.11 \frac{f^2}{1+f^2} + 44 \frac{f^2}{4100+f^2} + 2.75 \times 10^{-4} f^2 + 0.003$ [15]. When considering multiple propagations, the Channel Transfer Function (CTF) of each path is $H_p(f) = \Gamma_p / \sqrt{A(l_p, f)}$, where Γ_p is the cumulative reflection coefficient. Therefore, the overall CTF with multipath

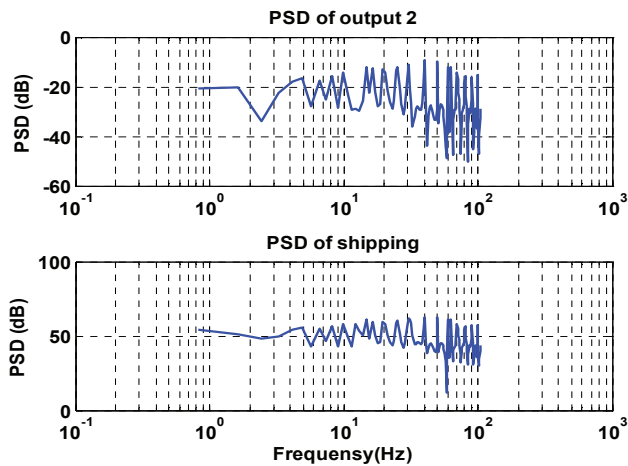


Fig. 8: Power Spectral Density (PSD) of the output (top) and of the original shipping noise (bottom).

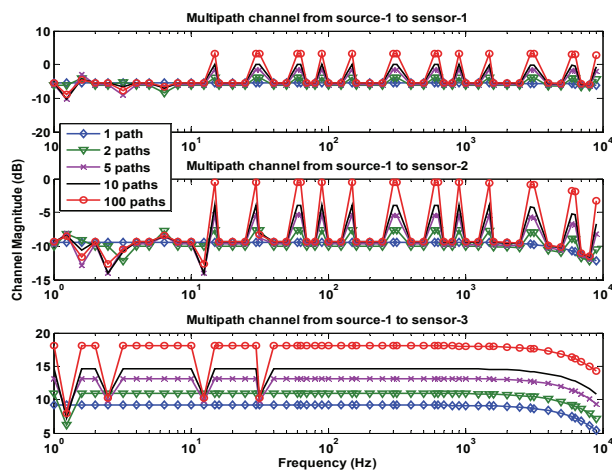


Fig. 9: Channel magnitude response for different multipath environments from source 1 to each of the other three sensors.

is calculated as $H(f) = \sum_p H_p(f)e^{-j2\pi f\tau_p}$ in which τ_p represents the propagation delay associated with the path. In Fig. 9, we plot the CTF for the channel between different sensors as the receiver and a sample noise source for varying degrees of multipath. For this figure, we assumed the distances from the source to sensors 1, 2 and 3 to be 2, 11, and 15 Km, respectively. Regarding this figure, the increase in Transmission Loss (TL, in dB) is higher for a lower number of multipath, e.g., the increase in TL from 1 to 5 paths is higher than from 5 to 10 path; in the presence of heavy multipath with hundreds of paths, in fact, the channel saturates, which can be modeled using Rayleigh fading.

IV. CONCLUSION AND FUTURE WORK

Human-generated acoustic noise has increased significantly over the past decade with the advancement in underwater communication technology. In this paper, we studied the problem of real-time separation and classification of human-generated or natural underwater acoustic-noise sources. We

presented an algorithm based on Blind Source Separation (BSS) to separate dominant sources (which does not need to first estimate the underwater channel), and for a fixed number of sources we showed its performance via simulations. Once separated, we also classified the sources by comparing their Power Spectrum Density (PSD) against that of known ones. Work is currently being conducted to validate the results and to localize the sources using real data collected from underwater acoustic communication testbeds.

A non-trivial yet interesting extension of this work would involve using Autonomous Underwater Vehicles (AUVs) as mobile receivers, which could not only collect more mixtures from multiple locations (assuming static sources) but also track sources of interest down by moving towards regions where the dominance of the mixing matrix increases.

REFERENCES

- [1] I. F. Akyildiz, D. Pompili, and T. Melodia, "Underwater acoustic sensor networks: research challenges," *Ad Hoc Networks*, vol. 3, no. 3, pp. 257–279, Mar. 2005.
- [2] *Ocean noise and marine mammals*. Committee on Potential Impacts of Ambient Noise in the Ocean on Marine Mammals, National Research Council, Ocean Studies Board, Division on Earth and Life Studies, Washington, DC: The National Academies Press, 2003.
- [3] R. P. Hodges, *Underwater acoustics: analysis, design, and performance of sonar*. John Wiley & Sons, 2011.
- [4] D. Green, H. DeFerrari, D. McFadden, J. Pearse, A. Popper, W. Richardson, S. Ridgway, and P. Tyack, "Low-frequency sound and marine mammals: current knowledge and research needs," *Washington, DC: National Research Council*, 1994.
- [5] B. Chen and D. Pompili, "QUO VADIS: QoS-aware underwater optimization framework for inter-vehicle communication using acoustic directional transducers," in *Proc. of the IEEE Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON)*, Salt Lake City, UT, Jun. 2011.
- [6] F. W. Machell, C. S. Penrod, and G. E. Ellis, *Statistical characteristics of ocean acoustic noise processes*. Springer, 1989.
- [7] G. M. Wenz, "Acoustic ambient noise in the ocean: spectra and sources," *The Journal of the Acoustical Society of America*, vol. 34, no. 12, pp. 1936–1956, 2005.
- [8] J. S. Panaro, F. R. Lopes, L. J. Matos, and L. M. Barreira, "Empirical noise model and likelihood metrics for underwater acoustic communications," in *Proc. of the IEEE Conference on Underwater Communications Networking (UComms)*, Sestri Levante, Italy, Sep. 2012.
- [9] P. van Walree, "Propagation and scattering effects in underwater acoustic communication channels," *IEEE Journal of Oceanic Engineering*, vol. 38, no. 4, pp. 614–631, Oct. 2013.
- [10] P. van Walree and R. Otnes, "Wideband properties of underwater acoustic communication channels," in *Proc. of the IEEE Conference on Underwater Communications Networking (UComms)*, Sestri Levante, Italy, Sep. 2012.
- [11] L. Parra and P. Sajda, "Blind source separation via generalized eigenvalue decomposition," *The Journal of Machine Learning Research*, vol. 4, pp. 1261–1269, Dec. 2003.
- [12] H. Viswanathan, E. K. Lee, I. Rodero, and D. Pompili, "An autonomic resource provisioning framework for mobile computing grids," in *Proc. of the ACM International Conference on Autonomic Computing (ICAC)*, San Jose, CA, Sep. 2012.
- [13] G. C. Carter, C. Knapp, and A. H. Nuttall, "Estimation of the magnitude-squared coherence function via overlapped fast fourier transform processing," *IEEE Transactions on Audio and Electroacoustics*, vol. 21, no. 4, pp. 337–344, Aug. 1973.
- [14] P. Qarabaqi and M. Stojanovic, "Statistical characterization and computationally efficient modeling of a class of underwater acoustic communication channels," *IEEE Journal of Oceanic Engineering*, vol. 38, no. 4, pp. 701–717, 2013.
- [15] L. M. Brekhovskikh, P. Lysanov, and Y. P. Lysanov, *Fundamentals of ocean acoustics*. Springer, 2003.