Proceedings of 20th International Congress on Acoustics, ICA 2010

23–27 August 2010, Sydney, Australia

Acoustic sensing in snapping shrimp dominated environments

Mandar Chitre

ARL, Tropical Marine Science Institute and
Department of Electrical & Computer Engineering
National University of Singapore

PACS: 43.30.Nb, 43.60.Cg, 43.80.Ka

ABSTRACT

Snapping shrimp dominate the high frequency soundscape in shallow warm waters. The noises produced by these small creatures are a result of the collapse of cavitation bubbles they produce. During the rapid collapse, the temperatures in the bubble can momentarily reach the surface temperature of the sun, and produce impulsive noise with source levels higher than 190 dB re 1 μPa @ 1m. With millions of snapping shrimp in most warm shallow water environments, the resulting cacophony is heard in the form of a background crackle familiar to many tropical divers. The resulting ambient noise has highly non-Gaussian statistics. What implications does this have on acoustic sensing in these environments? Can signal processing techniques developed with Gaussian noise assumptions be used without significant penalty in these environments? Can these shrimp be used as sources of opportunity for sensing? To begin answering some of these questions, we present a review of some of the research on signal processing in impulsive noise. Snapping shrimp noise is modeled accurately by symmetric α-stable distributions. Optimal signal processing in α-stable noise is often computationally infeasible, but computationally simple near-optimal solutions can be applied with gains up to 5-10 dB. Communicating in environments with snapping shrimp noise has its own challenges. The errors due to the impulsive noise on sub-carriers of a multi-carrier communication system, or the in-phase and quadrature channels of a single carrier system are not independent. If handled inappropriately, forward error correction codes can perform poorly in such systems. However, if the dependence in the errors can be characterized, it can be exploited in the decoding process to get substantial communication performance gains. We show this through an information theoretic analysis of the communication channel with additive symmetric α-stable noise. Finally, we turn to some applications where the snapping shrimp sounds can be used as sources of opportunity. They can serve as "illumination" for ambient noise imaging, where underwater objects can be imaged completely passively. They can also be used as sources for geoacoustic inversion of the surface sediment. We present some results from past experiments to show how sediment sound speed can indeed be inferred by simply listening passively to the cacophony of the shrimp.

INTRODUCTION

Snapping shrimp (family Alpheus and Synalpheus) dominate the high frequency soundscape in shallow warm waters. They 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 (Versluis et al. 2000). During the rapid collapse, the temperatures in the bubble can momentarily reach the surface temperature of the sun (Lohse et al. 2001), and produce impulsive noise with peak-to-peak source levels higher than 190 dB re 1 μPa @ 1m (Au and Banks 1998, Koay et al. 2003). The permanent crackling background noise in warm shallow waters throughout the world is attributed to numerous snaps from millions of shrimp inhabiting these waters. At low frequencies, noise from shipping is significant; above 2 kHz snapping shrimp noise dominates (Potter et al. 1997c). As ambient snapping shrimp noise is composed of impulsive noise sources, the resulting noise statistics are highly non-Gaussian (Nielsen and Thomas 1989, Potter et al. 1997a, Chitre et al. 2006).

Several noise models have been put forward to model the statistics of snapping shrimp dominated ambient noise. The power distribution of the noise is shown to be closely approximated by the log-normal distribution (Potter et al. 1997a, Potter and Chitre 1999). In signal processing applications, we are often interested in the amplitude distribution rather than the power distribution; the power distribution can easily be derived from the amplitude distribution if desired. Several amplitude distribution models such as the Gaussian-Gaussian mixtures, Gaussian-Garnele mixtures, Cauchy and α-stable have been tested against data from various shallow warm water locations (Chitre et al. 2006, Legg 2010). Of these, the symmetric α-stable (SαS) model has been found to model most data sets accurately with only a few parameters. Moreover the use of the model is also motivated by a strong theoretical basis given by the *generalized central limit theorem*, which states that the sum of i.i.d. random variables with or without a finite variance converges to a stable distribution by increasing the number of variables (Samorodnitsky and Taqqu 1994). We therefore use this model throughout this paper, although the key arguments made remain unchanged even under other impulsive noise models. In addition to the amplitude distribution, the temporal dependence of the noise process is also of importance in signal processing. Various models for the temporal dependence have been explored by Legg (2010).

We ask the following questions in light of the highly non-Gaussian ambient noise found in warm shallow waters: What implications does the non-Gaussian noise have on acoustic sensing? Can signal processing techniques developed with Gaussian noise assumptions be used without significant penalty? Can these shrimp be used as sources of opportunity for sensing? The first question forms the theme of the paper and is answered throughout the paper. The second question has a clear negative answer as we shall demonstrate in the next section. With appropriate non-Gaussian noise based signal processing, we can reap significant benefits – and in many cases, the resulting signal processing algorithm is simple to implement. Encouragingly, the last question has a positive answer and we review a few research findings where snapping shrimp have been used as sources of opportunity.

SIGNAL PROCESSING & COMMUNICATION

In this section, we review a few key results in signal processing and communication in the presence of snapping shrimp noise (modeled as SαS noise).

Symmetric α-stable noise distribution

The impulsive nature of snapping shrimp noise results in large-amplitude excursions from the average more frequently than in the case of Gaussian noise. The probability density function (PDF) of 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 (Samorodnitsky and Taqqu 1994). Stable distributions are a direct generalization of the Gaussian distribution and include the Gaussian distribution as a limiting case. The characteristic exponent ($0 < \alpha \leq 2$) of the distribution controls the heaviness of the tails. A small positive value for α represents a highly impulsive distribution while α close to 2 indicates Gaussian-like behavior. When $\alpha = 2$, the distribution reduces to a Gaussian distribution. An important subclass of the stable distributions is the SαS distribution, which is well-suited to describe the observed zero-mean symmetric heavy tailed PDF of the snapping shrimp noise. Most snapping shrimp data sets are best described by SαS distributions with values of α in the range of 1.5 to 1.98 (Chitre et al. 2006, Legg 2010).

The SαS distribution is most conveniently described by its characteristic function:

$$\phi_\alpha(\omega;c) = e^{-|c\omega|^\alpha} \tag{1}$$

where α is the characteristic exponent and c is a scale parameter. The PDF $f_\alpha(x;c)$ of the distribution with a characteristic function $\phi_\alpha(\omega;c)$ is given by

$$f_\alpha(x;c) = \frac{1}{2\pi}\int_{-\infty}^{\infty} \phi_\alpha(\omega;c)e^{i\omega x}d\omega \tag{2}$$

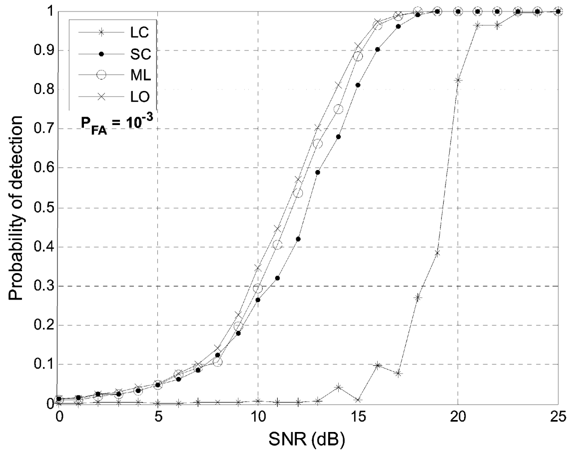
The SαS distribution does not have a general closed-form PDF $f_\alpha(x;c)$ or cumulative distribution function (CDF) $F_\alpha(x;c)$ except in the special cases of Cauchy ($\alpha = 1$) and Gaussian ($\alpha = 2$) distributions. Efficient numerical approximations allow computation of the PDF for other values of α (Nolan 1997, McCulloch 1998).

Signal detection

The problem of detecting a known signal with unknown amplitude in noise is commonly encountered in many applications. If the known signal x_t with an amplitude A is present in the observed data y_t, we have

$$y_t = Ax_t + n_t \tag{3}$$

where n_t is the noise. 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 familiar linear correlator (LC) (Tsihrintzis and Nikias 1995).



Source: Chitre et al. (2006)

Figure 1: Detection performance of various detectors (ML, LC, LO and SC) at a false alarm probability (P_{FA}) of 10^{-3} in snapping shrimp noise.

Unlike the 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. Nielsen and Thomas (1989) explored the use of non-parametric detectors in snapping shrimp noise but concluded that the LC performed better than the non-parametric techniques that they tried. Bertilone and Killeen (2001) modeled snapping shrimp noise using a Gaussian-Gaussian mixture and found that locally optimal (LO) detectors performed better than the LC at low SNR. The LO detector is parametric and requires detailed knowledge of the noise parameters. Chitre et al. (2006) showed that snapping shrimp noise can be described accurately by the SαS distribution and demonstrated that optimal (ML and LO) detectors based on the SαS distribution perform approximately 5-10 dB better than the LC in such noise environment. They also showed that the nonparametric sign correlation (SC) detector is a near-optimal alternative with typically less than 1 dB loss as compared to the ML detector (see Figure 1). The output T of the SC detector is simple to compute from the known signal x_t and the observed data y_t:

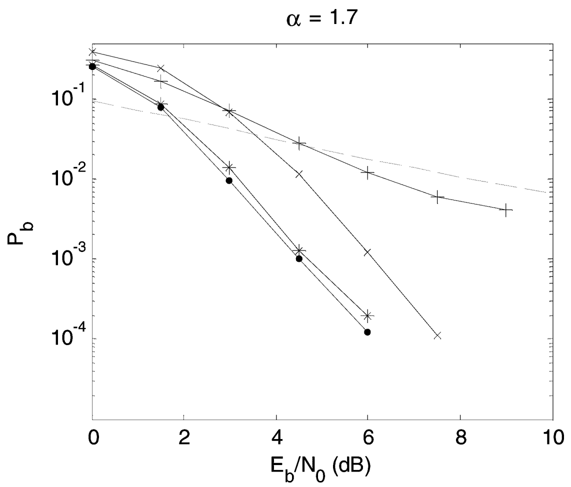
$$T = \sum_t \mathrm{sgn}(y_t)x_t \tag{4}$$

where sgn(x) is the signum function with a value 1 when x is positive, -1 when x is negative and 0 otherwise. The output is compared to a predetermined threshold to decide whether the observed data y_t contains the known signal x_t.

Since the SC detector is non-parametric, is very simple to implement and yields significantly better performance than the LC detector in presence of impulsive noise, it is suited to many signal detection tasks in snapping shrimp dominated waters.

Coherent communications

The performance of coherent communication systems such as phase-shift keying (PSK) in additive white Gaussian noise (AWGN) is well understood (Bernard 2001). The performance of various forward error correction (FEC) codes in such channels has also been extensively studied. However, the performance of these modulation and FEC schemes in presence of impulsive noise generated by snapping shrimp has received very little attention. Chitre et al. (2007) analyzed the performance of bipodal signaling schemes (such as binary PSK) in



Source: Chitre et al. (2007)

Figure 2: The performance of Viterbi decoding of convolutional codes using various distance metrics in presence of additive SαS noise. The x-axis shows the E_b/N_0 ratio commonly used in communication systems in place of SNR, while the y-axis shows the probability of bit error (P_b). The uncoded system performance is shown as a dashed line. In contrast, the hard decision decoding is shown as a solid line with cross, Euclidean metric decoding is shown as a solid line with plus markers, the 1-norm metric decoding is shown as a solid line with star markers, and the maximum likelihood decoding is shown as a solid line with dots.

SαS noise and showed that even a small degree of impulsiveness can have a large impact on the performance of an uncoded communication system. FEC codes (such as block codes, convolutional codes, LDPC codes, etc) are often used to combat the errors introduced by the noise in the channel. In the same paper (Chitre et al. 2007), the authors analyzed the performance of convolutional codes decoded using the classical Viterbi algorithm (Johannesson and Zigangirov 1999). They showed that the soft decision Viterbi algorithm with a Euclidean distance metric, known to be optimal in Gaussian noise, performs poorly in SαS noise when $\alpha < 2$. The hard decision version of the algorithm (using a Hamming distance metric) performs significantly better. A maximum likelihood Viterbi decoding is possible, but computationally infeasible. However, a novel soft-decision version using a 1-norm distance metric outperforms both the Euclidean distance and the Hamming distance versions, without adding any computational complexity to the decoding process (see Figure 2).

Although explicitly analysis for other modulation schemes and FEC codes is as yet unavailable, it is clear that modifications are needed to the detection and decoding algorithms in communication systems to cope with the SαS noise generated by snapping shrimp. In fact, as we shall see in the next section, we may need significant changes to the modulation schemes and the FEC codes used (not just limited to the detection and decoding algorithms) in order to achieve the best communication performance in snapping shrimp noise.

Multi-channel communications

In the last section, we briefly looked at the performance of BPSK in an SαS noise channel. A quadrature PSK (QPSK) communication system (with Grey codes) can be viewed as a pair of orthogonal BPSK systems being used simultaneously, and therefore we would expect the QPSK system to be able to carry twice as much data as the BPSK system. Indeed this is true in the case of Gaussian noise channels, where the noise in the in-phase and quadrature channels of the QPSK system are also Gaussian and independent. As noted by Chitre and Armand, when the channel noise is SαS (with $\alpha < 2$), this is no longer true – the noise in the in-phase and quadrature channels is no longer independent. If the dependency is used to correct errors, the data carrying capacity of the QPSK system can exceed twice the data carrying capacity of the equivalent BPSK system. In order to exploit this dependency, the FEC codes need to be appropriately designed and decoded.

An information theoretic analysis of a QPSK system in SαS noise is presented by Chitre and Armand. We do not reproduce the analysis but outline the main arguments here. The differential entropy (or just *entropy*, measured in bits) of a real-valued SαS noise with PDF $f_\alpha(x;c)$ is given by

$$H_{\alpha,c} = -\int_{-\infty}^{\infty} f_\alpha(x;c)\log_2 f_\alpha(x;c)dx \tag{5}$$

Since the PDF does not have a closed-form expression, we numerically compute the entropy of the noise as a function of α in Figure 3. The channel capacity of an real-valued additive SαS noise channel is given by

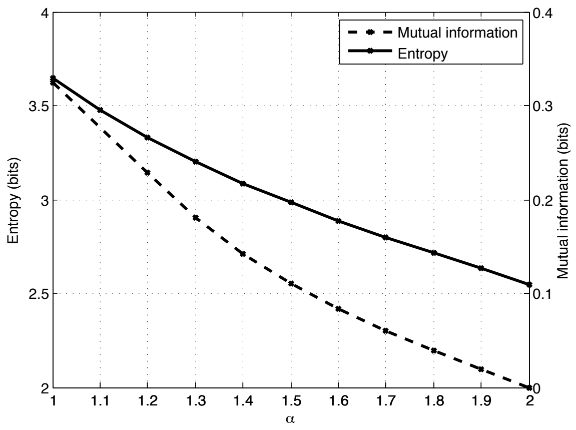
$$C_\alpha = \max\left(H_Y - H_{\alpha,c}\right) \tag{6}$$

where H_Y is the entropy of the received signal (source signal plus noise) and the maximization is carried out over all possible source signal PDFs. The real-valued channel can be used to model a BPSK system. We can therefore expect that the capacity of the additive SαS noise BPSK system reduces as α reduces (noise becomes more impulsive) and the noise entropy $H_{\alpha,c}$ increases. This analysis can be applied to a QPSK system by allowing the signal and the noise to be complex-valued, where the real and imaginary components represent the in-phase and quadrature channels respectively. Due to symmetry considerations, we expect that the complex noise is isotropic (rotationally invariant). Although the real and imaginary components of complex-valued isotropic Gaussian noise are independent, the components of complex-valued isotropic SαS noise ($\alpha < 2$) are not (Samorodnitsky and Taqqu 1994). The entropy $\tilde{H}_{\alpha,c}$ of the complex-valued SαS noise can be expressed in terms of the equivalent real-valued SαS noise entropy and mutual information I_α shared by the the channels due to the dependency in the PDF:

$$\tilde{H}_{\alpha,c} = 2H_{\alpha,c} - I_\alpha \tag{7}$$

Again, the mutual information I_α cannot be evaluated in closed form, but can be numerically evaluated (see Figure 3). If the in-phase and quadrature channels in a QPSK system are treated separately as real-valued channels, the total noise entropy is $2H_{\alpha,c}$. However, the noise entropy of the complex-valued channel is $2H_{\alpha,c} - I_\alpha$, and therefore its capacity is higher than the sum of the two component BPSK channel capacities. If the noise dependency is correctly utilized, the capacity increase can be harnessed for a communication system. As seen from Figure 3, the loss due to increased entropy is almost cancelled by the increased mutual information as α reduces from 2 to 1. Thus the capacity of a QPSK system in additive SαS noise is not much less than that in Gaussian channels provided the communication scheme (modulation and FEC code) is able to use the dependency in the noise. Chitre and Armand suggest an approach to exploit this dependency through the use of quaternary alphabets in the design of FEC codes.

When a multi-carrier communication (such as OFDM) system operates in a SαS noise channel, we need to consider the dependency of the noise across sub-carriers. Due to the broadband nature of impulsive snaps from snapping shrimp, the noise on various sub-carriers in the multi-carrier system is dependent (Chitre



Source: Chitre and Armand

Figure 3: Entropy H_α and mutual information I_α for of SαS noise for $c = 1$ and $1 \leq \alpha \leq 2$ (numerically evaluated). For arbitrary values of c, the entropy $H_{\alpha,c} = H_\alpha + \log_2 c$.

et al. 2005). Moreover, the in-phase and quadrature channels at each frequency are also dependent as outlined before. If an FEC code and decoding system is designed to take into account all of these dependencies, perhaps the multi-carrier communication system may significantly outperform an equivalent system in Gaussian noise. However, the information theoretic analysis or practical implementation of such a system is not presently available to the best of our knowledge.

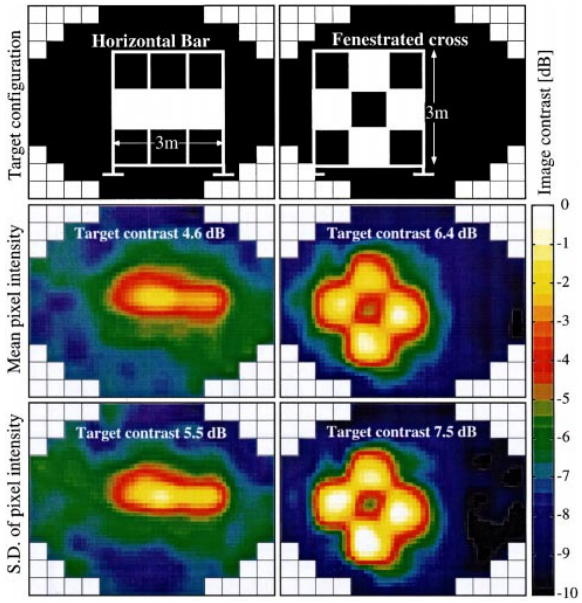
SOURCES OF OPPORTUNITY

So far we have considered snapping shrimp as a source of noise – something to contend with and mitigate the effects of. We now turn to the possibility that the sound produced by the snapping shrimp can be used to our benefit. Marine mammals and fish have millions of years of evolution to learn to use snapping shrimp sounds, so we would not be surprised if they have already developed ways to use this sound to their own advantage (Simpson et al. 2005, Potter et al. 1997b, Potter and Chitre 2006, Taylor et al. 1997). We next present two different applications where snapping shrimp are used as sources of opportunity.

Ambient noise imaging

The idea of using ambient noise as a form of "acoustic illumination" for underwater sensing was explored theoretically almost two decades ago (Buckingham et al. 1992). To draw a parallel to our use of daylight for optical sensing, the idea was termed as *acoustic daylight*. The first system (known as ADONIS) to test this idea was built at the Scripps Institute of Oceanography (Buckingham et al. 1996). ADONIS was successfully able to image targets at ranges of about 40 m passively using the ambient noise generated by snapping shrimp that dominate the high-frequency soundscape around La Jolla, San Diego. The acoustic daylight images were produced by time-averaging the energy received at the camera from different directions. Targets present in the field of view reflect sounds incident from different directions as compared to the background. When the acoustic illumination is spatially anisotropic, this produces a contrast between the targets and the background, allowing the targets to become clearly visible in the image. However, when the illumination is not favorable, the targets cannot be seen in the resulting image.

Potter and Chitre (1999) studied the data generated by ADONIS further and showed that the energy distribution of each pixel in the image can be approximated by a log-normal PDF. Since



Source: Potter and Chitre (1999)

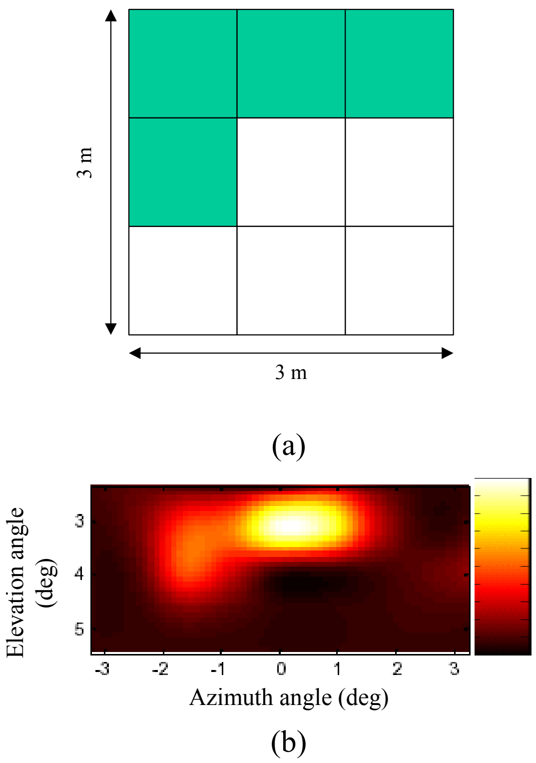
Figure 4: Horizontal bar and fenestrated cross targets from ADONIS experiment, shown schematically in the upper panels, with ambient noise images formed from the first (mean) and second-order (s.d.) moments shown in the lower panels.

the log-normal distribution is characterized by two independent parameters, the authors were able to generate images by not just time-averaging the data, but also from the second-order moment of the power distribution (see Figure 4). By using the two independent ways to extract information from each pixel and applying a Kalman filter to track the pixel values, the effect of occasional unfavorable illumination could be further mitigated to produce images more consistently. Had the ambient noise been Gaussian distributed (with a zero mean), its power would be χ^2 distributed and characterized by a single parameter. Thus the higher-order moment based imaging is a direct consequence of the non-Gaussian nature of the snapping shrimp noise illumination. The work by Potter and Chitre (1999) was further extended by Lim and Potter (2002) to iteratively enhance the images and fuse data through the use of clustering algorithms.

Inspired by the success of ADONIS, a second-generation ambient noise imaging camera (named ROMANIS) was developed at the Acoustic Research Laboratory (ARL) of the National University of Singapore (Pallayil et al. 2003). Rather than use a focussing dish as used in ADONIS, ROMANIS uses a 2-dimensional phase array of 508 sensors, each sampled at about 196 kSa/s. Unlike ADONIS where only the power measured in selected frequency bands and pre-formed beams is recorded, ROMANIS records pressure time-series data from all 508 sensors. This yields a much richer data set for signal processing, allowing novel imaging techniques to be developed and tested. An initial deployment of ROMANIS in 2003 yielded images of a target placed at 70 m range (see Figure 5). Subsequent deployment in early 2010 has yielded images at ranges up to 120 m (unpublished results – under preparation for publication).

Geoacoustic inversion

Another example of the use of snapping shrimp as opportunistic sources is found in the work by Chitre et al. (2003). The authors assumed that the snapping shrimp lived near the sea bottom, and the "snap" typically recorded by a hydrophone in the water column consists of the combination of the direct arrival and the bottom-reflected arrival. Due to the bottom interaction, the



Source: Pallayil et al. (2003)

Figure 5: A schematic of a "sleeping L" target and an ambient noise image formed at 70 m range during the first ROMANIS deployment.

recorded snap contains information about the acoustic properties of the superficial sediment on the sea bottom. By using a tetrahedral array of 4 hydrophones, the authors identified the direction of arrival of each snap. By matching the recorded snap to a model of an "ideal" snap, the authors jointly estimated the height of the cavitation bubble collapse above the sea bed and the angle of interaction with the sea bed. By estimating the energy in the bottom-reflected arrival and plotting it against the angle of interaction with the sea bed, the critical angle was determined. The large numbers and spatially distributed nature of snaps allow many angles of interaction to be sampled in a short period of time. The authors further augmented the samples by also considering surface reflected arrivals which also contain bottom-surface interactions and provide information at much higher bottom-interaction angles. Once the critical angle is known, it can easily be translated to a sound speed in the sea bed.

Although the paper only estimates sound speed in the bottom, it provides evidence that passive geoacoustic inversion using snapping shrimp sounds as opportunistic sources may be feasible. The sheer number of snapping shrimp that inhabit warm shallow waters ensure that a large angular space can be sampled in a very short time without having to move the receiver. This may be ideal for rapid environment assessment applications where a few key sea bed parameters can be measured by simply deploying a small static hyrdrophone array.

CONCLUSIONS

In this paper, we reviewed some of the work on sensing in snapping shrimp dominated noise environments. The key point is that we can obtain significant gains by processing signals in snapping shrimp noise by appropriate signal processing techniques designed for impulsive noise. Near-optimal processing techniques need not be computationally complex, and are often very simple to implement. An information theoretic analysis suggests that communication systems can gain very significantly from appropriate design of FEC codes that take the impulsive nature of the noise into consideration. We also reviewed two applications where the snapping shrimp sounds are used to our benefit, rather than being treated as noise. The first application is that of ambient noise imaging, where passive targets in water can be acoustically imaged without any artificial insonification. The second application is that of rapid geoacoustic inversion by using snapping shrimp as opportunistic sources. Although the body of work on signal processing in snapping shrimp noise, or using the noise to our advantage, is small, it is compelling. We hope to see some of these ideas applied in practical systems in time to come.

REFERENCES

W. W. L. Au and K. Banks. The acoustics of the snapping shrimp synalpheus parneomeris in kaneohe bay. *The Journal of the Acoustical Society of America*, 103(1):41–47, 1998.

S. Bernard. Digital communications: Fundamentals and applications, 2001.

D. Bertilone and D. Killeen. Statistics of biological noise and performance of generalized energy detectors for passive detection. *Oceanic Engineering, IEEE Journal of*, 26(2): 285 –294, apr 2001. ISSN 0364-9059. doi: 10.1109/48.922794.

M. J. Buckingham, B. V. Berkhout, and S. A. L. Glegg. Imaging the ocean with ambient noise. *Nature (London)*, 356:327–329, 1992.

M. J. Buckingham, J. R. Potter, and C. L. Epifanio. Seeing in the ocean with background noise. *Scientific American*, 274 (2):86–90, 1996.

M. Chitre and M. A. Armand. On the capacity and code alphabet for complex baseband channels with α-stable noise. (submitted).

M. Chitre, T. B. Koay, and J. Potter. Origins of directionality in snapping shrimp sounds and its potential applications. In *OCEANS 2003 IEEE/MTS*, San Diego, USA, 2003.

M. Chitre, S. H. Ong, and J. Potter. Performance of coded ofdm in very shallow water channels and snapping shrimp noise. In *OCEANS, 2005 MTS/IEEE*, pages 996–1001 Vol. 2, 2005.

M. Chitre, J. R. Potter, and S. H. Ong. Viterbi decoding of convolutional codes in symmetric α-stable noise. *Communications, IEEE Transactions on*, 55(12), 2007.

M. A. Chitre, J. R. Potter, and S. H. Ong. Optimal and near-optimal signal detection in snapping shrimp dominated ambient noise. *Oceanic Engineering, IEEE Journal of*, 31(2): 497–503, 2006.

R. Johannesson and K. Zigangirov. *Fundamentals of convolutional coding*. Wiley-IEEE press, 1999.

T. B. Koay, E. T. Tan, M. Chitre, and J. R. Potter. Estimating the spatial and temporal distribution of snapping shrimp using a portable, broadband 3-dimensional acoustic array. In *OCEANS 2003 IEEE/MTS*, San Diego, USA, 2003.

M. W. Legg. *Non-Gaussian and non-homogeneous Poisson models of snapping shrimp noise*. PhD thesis, Curtin University of Technology, February 2010.

C. K. Lim and J. R. Potter. Ambient noise imaging; enhanced spatial correlation algorithms and a way to combine independent images for improved stability and false alarm rate. In *Proceedings of Underwater Technology 2002*, pages 196–201, Tokyo, Japan, 2002.

D. Lohse, B. Schmitz, and M. Versluis. Snapping shrimp make flashing bubbles. *Nature*, 413(6855):477–478, 10 2001.

J. H. McCulloch. Numerical approximation of the symmetric stable distribution and density. In *A practical guide to heavy tails: statistical techniques and applications*, pages 489–499. Birkhauser Boston Inc., Cambridge, MA, USA, 1998. ISBN 0-8176-3951-9.

P. A. Nielsen and J. B. Thomas. Non-parametric detection in underwater environments. In *Acoustics, Speech, and Signal Processing, 1989. ICASSP-89., 1989 International Conference on*, pages 2728–2731, 1989.

J. P. Nolan. Numerical calculation of stable densities and distribution functions. *Communications in Statistics - Stochastic Models*, 13:759–774, 1997.

V. Pallayil, M. A. Chitre, E. T. Tan, J. Potter, T. B. Koay, S. B. Ruiz, and S. P. Tan. Ambient noise imaging – first deployments of romanis and preliminary data analysis. In *OCEANS 2003 IEEE/MTS*, San Diego, USA, 2003.

J. R. Potter and M. Chitre. Ambient noise imaging in warm shallow seas; second-order moment and model-based imaging algorithms. *The Journal of the Acoustical Society of America*, 106(6):3201–3210, 1999.

J. R. Potter and M. A. Chitre. Do fish fry use emergent behaviour in schools to find coral reefs by sound? In *AGU Ocean Sciences Meeting*, Honolulu, Hawaii, February 2006.

J. R. Potter, T. W. Lim, and M. A. Chitre. Ambient noise environments in shallow tropical seas and the implications for acoustic sensing. In *Oceanology International '97, Singapore*, 1997a.

J. R. Potter, E. Taylor, and M. A. Chitre. Could marine mammals use ambient noise imaging techniques? In *134th Acoustical Society of America Meeting*, San Diego, USA, 1997b.

J. R. Potter, L. T. Wei, and M. A. Chitre. High-frequency ambient noise in warm shallow waters. In *Sea Surface Sound, UK*, 1997c.

G. Samorodnitsky and M. S. Taqqu. *Stable Non-Gaussian Random Processes*. Chapman and Hall, New York, NY, USA, 1994. ISBN 0412051710.

S. D. Simpson, M. Meekan, J. Montgomery, R. McCauley, and A. Jeffs. Homeward sound. *Science*, 308(5719):221, 2005.

E. Taylor, J. R. Potter, and M. A. Chitre. Ambient noise imaging potential of marine mammals. In *Bioacoustics Conference*, Loughborough, UK, 1997.

G. Tsihrintzis and C. Nikias. Performance of optimum and suboptimum receivers in the presence of impulsive noise modeled as an alpha-stable process. *Communications, IEEE Transactions on*, 43(234):904 –914, feb/mar/apr 1995. ISSN 0090-6778. doi: 10.1109/26.380123.

M. Versluis, B. Schmitz, A. von der Heydt, and D. Lohse. How snapping shrimp snap: through cavitating bubbles. *Science*, 289(5487):2114, 2000.