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SNAPPING SHRIMP DOMINATED NATURAL SOUNDSCAPE IN SINGAPORE WATERS

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ABSTRACT. — Snapping shrimp dominate the high frequency soundscape in the warm shallow waters around Singapore. 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, the resulting cacophony is heard in the form of a background crackle familiar to many tropical divers. The resulting ambient noise has a heavy tailed pressure amplitude probability distribution. This has an adverse impact on the performance of acoustic sensing and communication systems that are developed using the commonly adopted Gaussian noise model. On the other hand, systems designed with a proper understanding of the snapping shrimp noise statistics are able to perform well in Singapore waters. Interestingly, snapping shrimp can also serve as sources of opportunity for acoustic sensing. For example, ROMANIS, an ambient noise-imaging camera developed at the Acoustic Research Laboratory, is able to image underwater objects using snapping shrimp noise as acoustic 'illumination'. To develop techniques for acoustic sensing in snapping shrimp dominated soundscapes, a good understanding of the spatio-temporal statistics of the noise made by these creatures is vital. We present statistical analysis of acoustic data from several experiments in Singapore waters. We discuss the spatial anisotropy that is observed and its implications on acoustic sensing. We also present point process models that accurately capture the observed temporal clustering of shrimp snaps.

INTRODUCTION

Snapping shrimp (genera *Alpheus* and *Synalpheus*) dominate the high frequency soundscape in warm shallow waters around Singapore (Potter et al., 1997a, c). 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 'snap' 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 exceeding 190 dB re 1 μPa @ 1m (Au and Banks, 1998, Koay et al., 2003). With millions of snapping shrimp contributing to the ambient noise in warm shallow waters, the resulting cacophony is heard in the form of a background crackle familiar to most tropical divers.

The loud snaps produced by the snapping shrimp disrupt the operations of underwater acoustic sensors, sonars and communication systems. Engineers wishing to develop acoustic systems for warm shallow water operations need to understand spatio-temporal statistics of the noise in order to better inform their design decisions. Essentially, they need to know when and where the snaps are likely to occur and how loud they are likely to be. Although an individual snap location, time and amplitude cannot be reliably predicted, we can make good predictions about the average snap density and arrival rate. We can also accurately predict the probability that a snap is louder than a specified amplitude threshold. Such statistical predictions are key to the design of robust acoustic systems for operation in snapping shrimp dominated waters of Singapore (Chitre et al., 2006). Snapping shrimp can also serve as sources of opportunity. A snap reflected off the seabed, for example, is modified by the seabed and contains some information about the sediment.

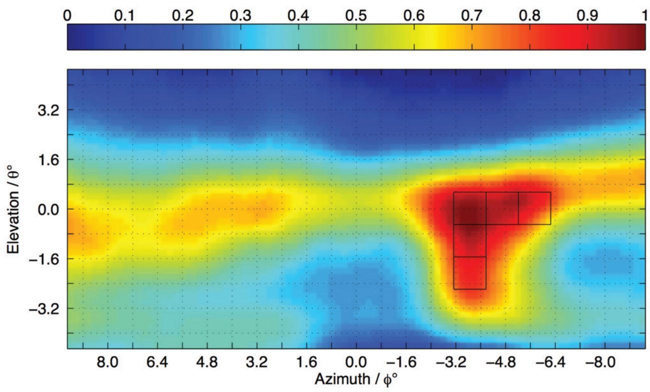
Thus, it is possible to simply listen to a large number of snaps and estimate seabed sediment properties (Chitre et al., 2003). A more striking application of snapping shrimp noise is the concept of ambient noise imaging (ANI). An acoustic camera designed using this concept utilizes snaps as acoustic 'illumination' to image underwater objects passively. To understand this concept better, consider the following analogy. We are able to photograph an object in daylight as the sun provides illumination that reflects off the object and reaches our camera. Snapping shrimp can be thought of as millions of tiny acoustic 'strobe lights' providing intermittent acoustic 'illumination' in the form of snaps. These snaps reflect off underwater objects and reach the ANI camera, which then produces images of the object. This idea was first theoretically explored almost two decades ago by Buckingham et al. (1992). ADONIS, an acoustic camera to test this idea, was built at the Scripps Institute of Oceanography. It was successfully able to image targets at ranges of about 40 m passively using the ambient noise generated by snapping shrimp living at the pier in La Jolla, San Diego (Buckingham et al., 1996; Epifanio et al., 1999; Potter & Chitre, 1999). ROMANIS (Fig. 1), a second-generation camera, was subsequently developed at the Acoustic Research Laboratory (ARL) in Singapore (Pallayil et al., 2003, Kuselan et al., 2010). Algorithms based on a statistical understanding of snapping shrimp noise were not only able to produce images (Fig. 2) of targets at 65 m using data collected by ROMANIS, but were also able to estimate the location of the target accurately (Chitre et al., 2012).

Fig. 1. The ROMANIS ambient noise imaging camera being deployed at sea in Singapore waters during a field experiment in 2010.

Simpson et al. (2005) showed that reef sounds were important in recruitment of fish larvae to the reef. Through numerical studies, Potter and Chitre (2006) showed that simple collective behaviors had the potential to allow larvae to localize reefs using the noise produced by them. Since the dominant noise from a reef is due to snapping shrimp, this finding suggests that snapping shrimp may be a keystone species in reef ecology. An understanding of the sound produced by the reefs may allow us to develop acoustic remote sensing technology for rapid mapping of the reefs, and for large scale monitoring of reef health. Such technology could augment and partially replace expensive and manpower-intensive dive surveys, and be used as an important tool for management of coral reefs.

To successfully employ acoustic sensing in snapping shrimp dominated waters, it is therefore essential to understand the statistics of snapping shrimp noise. Potter et al. (1997a, b) showed that the high-frequency ambient noise power in Singapore and other shallow tropical waters was approximately log-normally distributed. Chitre et al. (2006) studied the pressure amplitude distribution of the noise and found it to be accurately modeled by the stable family of distributions. While these observations are important, they do not characterize the noise fully. In order to explain the observed distribution, Potter and Koay (2000) asked an important question – is there temporal or spatial clustering

(a) A target frame with 1m x 1m closed-cell Neoprene foam Aluminum-backed reflector panels in an inverted L-shaped arrangement being deployed.



(b) An ambient noise image of the target in the 25-50 kHz band from a 1 second data segment.

Fig. 2. Target frame and ambient noise image of the target frame using ROMANIS during the 2010 field experiment.

in snap occurrences? To answer these questions, the ARL undertook a series of experiments and measurements in Singapore waters. In parallel, independent measurements in snapping shrimp dominated Australian waters have also shed some light on the subject (Legg, 2010). In this paper, we provide a summary of the key findings from our measurements in Singapore.

Spatial Distribution

We start by exploring the spatial distribution of snap occurrences. In order to answer the question on whether snaps are clustered in space, or uniformly distributed over large areas, we performed a series of experiments in Singapore waters. We present results from one such representative experiment from the Raffles Anchorage to the south of Singapore.

Methods. — In order to localize snaps, we developed HiDAQ, a device capable of recording good quality acoustic data from four hydrophones at a sampling rate of 500 kSa/s. The four hydrophones were mounted at the vertices of a regular tetrahedron with 1.1 m edges. The resulting tetrahedral hydrophone array was deployed, as illustrated in Fig. 3, at Raffles Anchorage from a barge using a spar buoy for stability. 20 minutes of data was recorded. The time of arrival of each snap at each of the hydrophones was estimated from the recorded data. Using the arrival times of a given snap on each hydrophone, the azimuth and elevation directions of arrival of that snap were estimated (Koay et al., 2003). Knowing the depth, altitude and orientation of the tetrahedral array, the local bathymetry, and assuming that snapping shrimps live near the bottom or on manmade structures (Johnson et al., 1947, Ferguson & Cleary, 2001), the arrival directions were used to compute the location of origin of each snap with respect to the array. From all the snaps in the recording, a local map of snap occurrences during the 20-minute period was produced.

Results. — Fig. 4 shows a directivity plot of arrivals. The plot was produced by time averaging the power in snaps arriving from various directions. It is evident from the plot that the noise is not isotropic, i.e., the noise power arriving from different directions is unequal. If we assume that snaps from various directions are (on an average) equally loud, there must be more snaps occurring in some directions as compared to others.

Fig. 5 shows a local map of estimated snap locations on the seabed, centered around the position of the tetrahedral array. Large variability in snap density is clearly seen in the map. The region to the southeast has an average snap density of 0.014 snaps s^{-1} m^{-2} and contributes to the large noise power

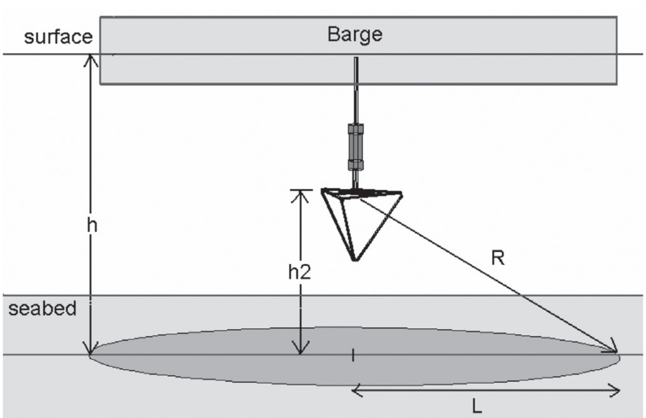


Fig. 3. An illustration of HiDAQ in the surface-mounted configuration using a spar buoy.

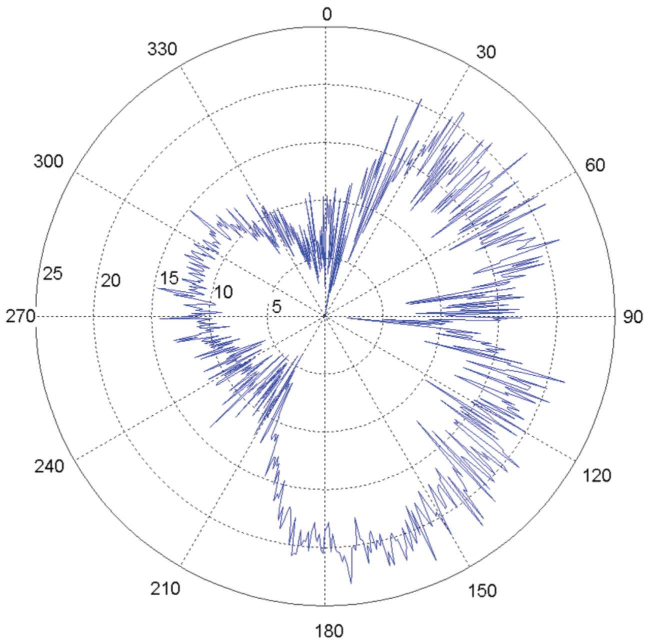


Fig. 4. A plot showing the directivity of snapping shrimp noise measured at Raffles Anchorage. The radial axis is marked in dB. The angular axis represents bearing in degrees where 0 corresponds to North.

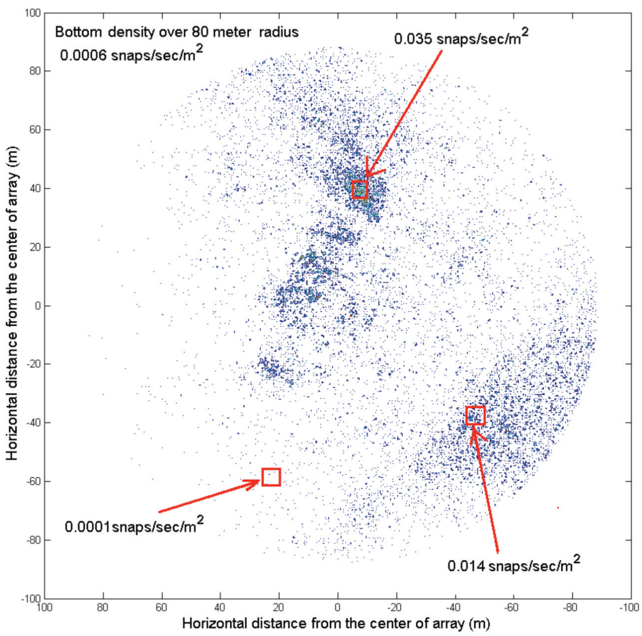


Fig. 5. Spatial distribution of snaps detected on the seabed during a 20 minute recording at Raffles Anchorage.

seen on the southeast in Fig. 4. The area to the northeast is smaller, but has a higher snap density of 0.035 snaps s^{-1} m^{-2}. The western regions have much fewer snap occurrences, with less than 0.0001 snaps s^{-1} m^{-2}. This indicates a high degree of spatial clustering, perhaps due to variability in available habitats, or due to existence of snapping shrimp colonies. Fig. 6 shows a local map of estimated snap locations on the sea surface; this is obtained by assuming that snaps arriving from above the array originate on the surface. Since we do not expect snapping shrimp to reside on the sea surface, we expect very few snaps (if any) to be seen in this plot. However, we observed a high density of snaps from a small rectangular localized area from the surface. On closer inspection, we found that this region coincided with the location of the barge from which the HiDAQ was deployed. It seemed that the bottom of the barge provided a good habitat for snapping shrimp to colonize!

Discussion. — The clustering of snap occurrences has important implications for acoustic sensing. For the application of mapping reefs or determining reef health, the clusters may directly provide information on the location of healthy reefs. For ANI, one would not expect much contrast between a target and the background in an isotropic environment, since the target would simply reflect similar noise from another direction. However, anisotropy potentially allows ANI to obtain a strong contrast between target and background. Hence the observed anisotropy ensures feasibility of ANI in tropical warm waters.

Amplitude statistics

Next, we explore the pressure amplitude probability distribution of snapping shrimp noise. This distribution is important in many signal processing applications, where a desired signal of interest has to be detected or processed in the presence of snapping shrimp noise. A common assumption in many signal processing applications is that the noise follows a gaussian probability distribution. This assumption is a poor one when the ambient noise is dominated by impulsive snaps (Fig. 7), and results in reduced performance of the signal processing algorithms. It has been found that symmetric α-stable (sαs) distributions are well suited to model the pressure amplitude probability distribution of snapping shrimp noise (Chitre et al., 2006). Here, we present results from statistical goodness-of-fit testing of acoustic data from another dataset recorded in Singapore waters.

Methods. —The ROMANIS ambient noise imaging camera has 508 hydrophones, each sampled at 196 kSa/s. The hydrophones are able to receive sounds between 25 kHz and 85 kHz. The hydrophones are slightly directional with a beamwidth of approximately 45 at the highest frequency, and a wider beam at lower frequencies. During the 2010 field experiments, ROMANIS was deployed at Selat Pauh in 15 m of water depth. We use recorded data from ROMANIS sensors to test the hypothesis that the pressure amplitude timeseries is drawn from a SαS distribution. We beamformed the data from ROMANIS using a conventional wideband delay-and-sum beamformer (Chitre et al., 2012) to create narrow beams of about 1 beamwidth in 288 different directions. We also use the data from the individual beams to test the hypothesis that the pressure amplitude timeseries of the beam is drawn from a SαS distribution.

Results. — Randomly chosen sensor data samples pass a χ^2 goodness-of-fit test for SαS distribution with characteristic exponent $\alpha \approx 1.5$ at a 5% level of significance. This suggests that the SαS family of distributions provide a good model for the pressure amplitude probability distribution of snapping shrimp noise. Samples of timeseries data at the output of the beamformer also passed chi-squared goodness-of-fit tests for SαS distribution with α between 1.5 and 2.0 depending on the beam direction. Beams pointed in directions where large number of shrimp can be heard are likely to be more impulsive (lower α) than beams pointed other directions.

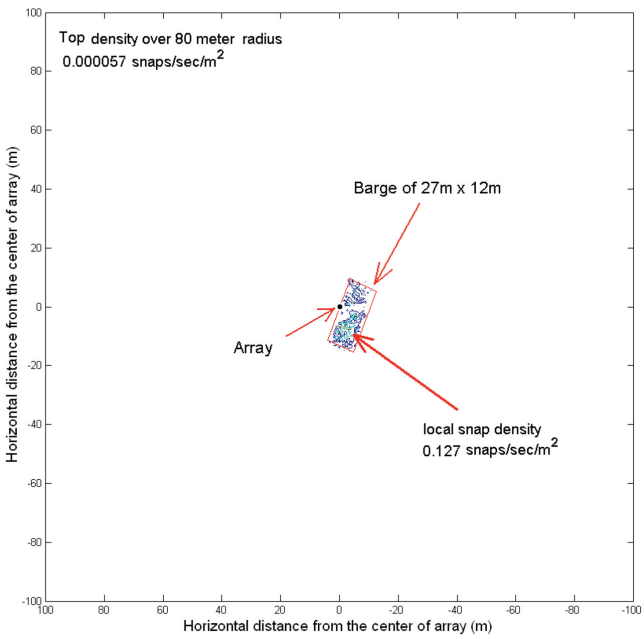


Fig. 6. Spatial distribution of snaps detected on the sea surface during a 20 minute recording at Raffles Anchorage.

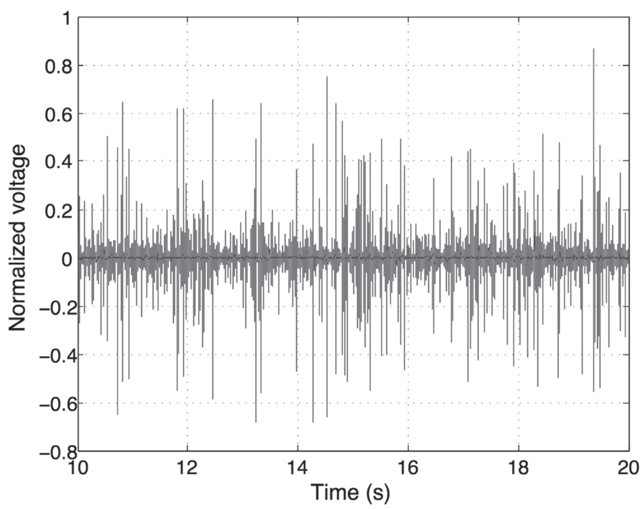


Fig. 7. A short section of ambient noise timeseries data from Singapore waters. The large frequent spikes due to snaps are clearly visible.

Discussion. — This SαS family of distributions arises out of the generalized central limit theorem, which states that the sum of a number of independent and identically distributed random variables with finite or infinite variance will tend to a stable distribution as the number of variables grows (Samorodnitsky and Taqqu, 1994). SαS distributions are characterized by two parameters – characteristic exponent α and scale parameter c. The characteristic exponent α controls the heaviness of the tails while the scale parameter c controls the width or spread of the distribution. When $\alpha = 2$, the distribution reduces to a Gaussian distribution, while $0 < \alpha < 2$ yield heavier tailed distributions. Except for the special cases of the Gaussian ($\alpha = 2$) and the Cauchy ($\alpha = 1$) distributions, the family of SαS distributions does not have a known closed-form probability density function. Instead, the distributions are expressed in terms of their characteristic function. Typical snapping shrimp noise environments have α in the range of 1.5 to 1.8. Signal processing and communication techniques developed for additive SαS noise (Shao and Nikias, 1993, Gonzalez and Arce, 1996, Kalluri and Arce, 1998, Chitre et al., 2006, 2007, Mahmood et al., 2012) can be used in the design of acoustic systems for warm shallow waters.

Temporal statistics

Lastly, we explore the temporal statistics of snapping shrimp noise. Essentially, we are concerned with the times when a snap is heard at a hydrophone.

Methods. — To investigate the snap times from a sample of ambient noise data, the pressure timeseries measured at the output of the hydrophone must be converted into a point process or spike-train. A spike-train is a collection of times that an event of some kind occurs; in the case of snapping shrimp noise, the events are snaps. To produce a spike-train, the snaps have to be detected. Detection of shrimp snaps is somewhat problematic because the snap acoustic signature has low energy and short duration. There is one characteristic of shrimp noise that admits a simple detection method: high pressure amplitude. The high amplitude pulses produced by snapping shrimp can be detected by setting a high threshold. The pulses are detected when the threshold is crossed. In this case the spike-train corresponds with level-crossings of the ambient noise. Level-crossing analysis of ambient noise in Singapore waters is expected to display characteristics that are dominated by the local snapping shrimp if the level crossing threshold is set at a suitably high amplitude. Obviously there will be always be some finite probability that the high amplitude was caused by something other than a shrimp snap, and these are false detections. For coastal data collected at a location in Singapore with low local shipping and boating noise, a low probability of activity from other high level click producing marine creatures (such as dolphins), and a high level of snapping shrimp activity, the assumption that most crossings of a high threshold level are caused by shrimp snaps can often be very good.

Given a spike-train of snaps, the investigation can proceed to explore both, the times between events, and the number of events in a defined amount of time. Techniques based on the times between events are called interval analysis, and techniques that use the number of events in a defined period are called counting analysis. Interval analysis techniques include the Inter-event Interval Histogram (IIH) (Perkel et al., 1967), the coefficient of variation (Nawrot et al., 2008), and kth order interval analysis (Brandman and Nelson, 2002). The simplest and possibly most important of these techniques is the IIH. An IIH considers only the time difference between each consecutive snap; these are the consecutive first-order intervals of the snaps. The IIH is then formed by computingan empirical histogram or estimate of the probability density of the intervals using a kernel method. If a suitable model can be found to fit the interval distribution then the snapping process can be understood. For example, if the interval distribution shows good agreement with an exponential distribution, then the snapping point process is most likely one of the Poisson family of process models. The importance of the IIH technique stems from the fact that if the process is a renewal process, then the distribution of consecutive first-order intervals completely characterizes the process (Perkel et al., 1967).

It is known that the snaps from snapping shrimp cannot be modeled as a pure renewal process with exponential intervals because the process does not conform with a homogeneous Poisson process (Legg, 2010). Further investigation of the snapping process must be conducted using techniques other than the IIH, including techniques that employ a counting analysis. The Fano-factor time curve is one such technique that is particularly useful when clustering occurs on relatively long time scales (long relative to the average inter-snap interval). The Fano-factor is defined as the variance to mean ratio of the counting process (Fano, 1947). When the Fano-factor is computed as a function of counting time the resulting curve is referred to as a Fano-factor time curve (Teich et al., 1996). The usefulness of the Fano-factor time curve stems from its expected result for a homogeneous Poisson process. For a homogeneous Poisson process, the Fano-factor is expected to equal one for all counting times. If the Fano-factor is observed to be greater than one then the snaps are clustered, and if the Fano-factor is less than one then the snaps are regular. An added benefit of the Fano-factor time curve is that the counting time can be directly related to the process time. Fano-factor deviations for a counting time of 5 seconds can be directly interpreted as clustering of the snaps over a time period of 5 seconds.

These two techniques, the interval based IIH and the count based Fano-factor time curve, were used to explore the temporal nature of snaps from a recording made off the eastern coast of Singapore. The noise sample was recorded at a sampling rate of 96 kSa/s for 20 minutes. The recording hydrophone was a RESON TC4013 miniature reference hydrophone with an acoustic bandwidth of more than 100 kHz, coupled with a preamplifier with bandwidth also in excess of 100 kHz.

Results and Discussion. — The noise sample was dominated by snapping shrimp noise. This was verified aurally and visually. The sample was also free of any significant interference and therefore suitable for shrimp noise analysis using only threshold detection. For consistency with Legg et al. (2007), we filtered the noise with a1 kHz cutoff high-pass filter and set the threshold to be 10 times the standard deviation of the noise beyond the mean. A sample of the timeseries used for the analysis is shown in Fig. 7.

Fig. 8 contains an IIH plot of probability density as a function of the inter-snap interval times. This plot contains useful information about how many different mechanisms are influencing the snap times, as well as revealing some of the nature of each mechanism.

The plot shows a collection of black circle points that are values computed from the measured data. When plotted on a semi-logarithmic axis there appear to be two distinctly different regions that look something like two straight lines. One of the lines has quite a steep slope at very short time intervals between events. The other line has a moderate slope and describes a relatively longer time scale. These two straight lines suggest two different mechanisms that can both be modeled as exponential distributions (due to the straight lines on a logarithmic scale) with different rates (due to the two different slopes). Theoretical curves for these two models are also shown in the plot. The solid blue line shows a model of the short time intervals with an average rate of 2160 snaps per second and the dashed red line shows a model of the medium time intervals with an average rate of 16.35 snaps per second. There is a higher rate of occurrence of short time intervals than medium time intervals. Short time intervals in these data refer to intervals that are less than 0.005 seconds (5 milliseconds). This time scale corresponds with a time scale that is strongly affected by multi-path arrivals and so a higher than expected number of short intervals is expected. Adding to this is the potential for multiple transitions of the threshold in the vicinity of a snap due to additive noise and 'ringing' after the main snap pulse caused by the highly reverberant shallow water propagation environment. Although these effects can be reduced by improving the snap detection method, their presence does not impose a burden to temporal analysis because they can be easily filtered. In this instance, the additional effort to improve detection is not warranted. Fig. 9 shows the IIH plot after filtering the short time intervals (black dot points) and a theoretical curve for the exponential distribution with rate 16.35 (red dashed line). Filtering the short time intervals allowed estimation of the distribution of intervals over medium times. The medium

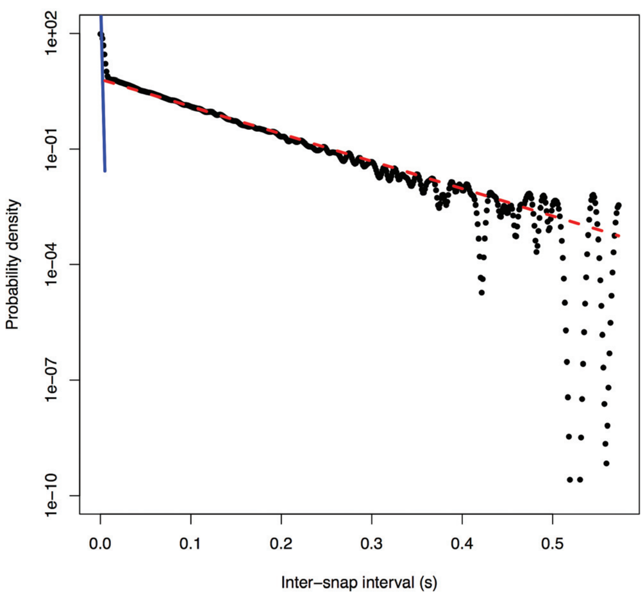


Fig. 8. Inter-snap interval densities for the raw level crossing spike-train (black dot points). Theoretical curves show a short time exponential density model with rate parameter 2160 snaps per second (solid blue line) and a medium time exponential density model with rate parameter 16.35 snaps per second (red dashed line).

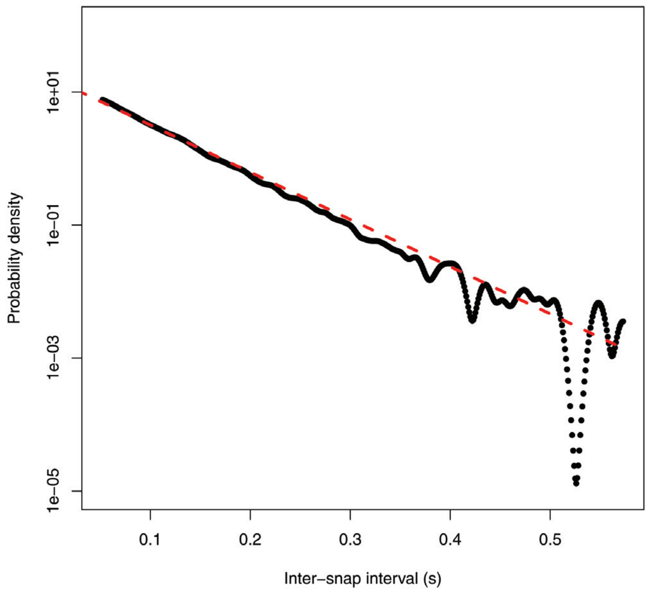


Fig. 9. Inter-snap interval densities for the filtered spike-train (black dot points) and an exponential density with rate parameter 16.35 snaps per second (dashed red line).

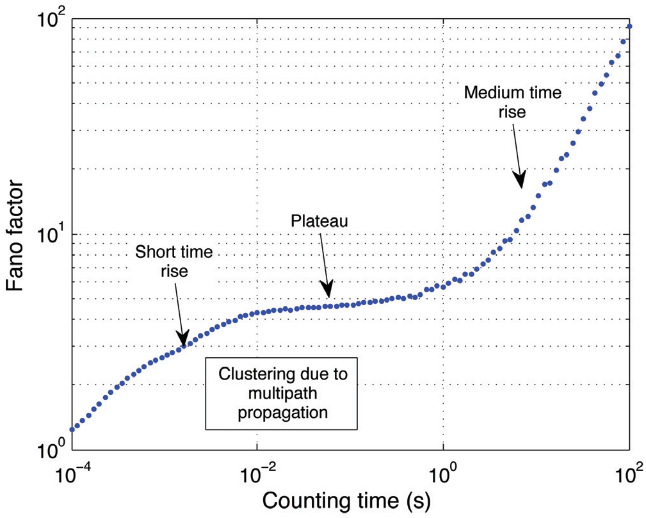


Fig. 10. Fano-factor time curve computed from the raw spike-train data (blue dot points). Three regions are evident in the plot, a short time rise, a short time plateau and a medium time rise. The short time rise is caused by multipath arrivals.

time model represents actual snaps from shrimp and the model allows us to claim that on average we should expect 16.35 snaps to occur with at least the threshold level every second. Increased variability in the IIH observation curves for longer intervals is due to low count numbers and does not need to be modeled.

Multipath propagation of the acoustic signal from a snap also introduces clustering onshort time scales. These clustered arrivals cause the Fano-factor time curve to deviation from a value of one at short times. Fig. 10 shows the Fano-factor time curve for the measured data. It is clear that the Fano-factor time curve deviates from one for counting times less than one second. The shape of the curve has a short time rise followed by a plateau. The plateau is an important feature because it confirms that the process causing the deviation is not a fractal process. Certain types of doubly stochastic Poisson processes that might be used to model the short time process have finite asymptotes that should coincide with the plateau. The plateau can also provide an important bound that assists with estimating model parameters.

Shrimp noise in Singapore waters also displays clustering on medium times (from 1 second to at least 100 seconds). This clustering can be seen in the Fano-factor time plot shown in Fig. 11. The Fano-factor time plot in this case has been computed from a spike-train that has been filtered to remove the short time effects. In this instance, the filtering was chosen to remove any intervals less than 0.005 seconds. The cause of medium time clustering in the shrimp noise is still unknown; however, a doubly stochastic Poisson model can be used to fit the Fano-factor time curve. This particular doubly stochastic Poisson model is driven by a type of correlated random process called a Cox-Ingersoll-Ross (CIR) process. A theoretical Fano-factor time curve for the model with CIR parameters a=0.0017, b=16.35 and σ=0.025 is shown using a red dashed line in Fig. 11. The theoretical curve is in good agreement with observation through the section of the curve that deviates to indicate clustering but the two curves do not agree at shorter times. The reason for this difference is the filtering that has been applied to the observations. At short counting times the model tends to the value one expected for a homogeneous Poisson process. This is because over very short periods the intensity of the Poisson process tends not to vary and so the process appears homogeneous over that short period. The observations, however, have been artificially adjusted to not allow short intervals so that the observed process seems to be more regular than would be expected for a homogeneous Poisson process. This can be accounted for exactly by using what is called a dead-time modified homogeneous Poisson process (Lowen & Teich, 1992); however, this level of detail is not required for modeling the medium time clustering.

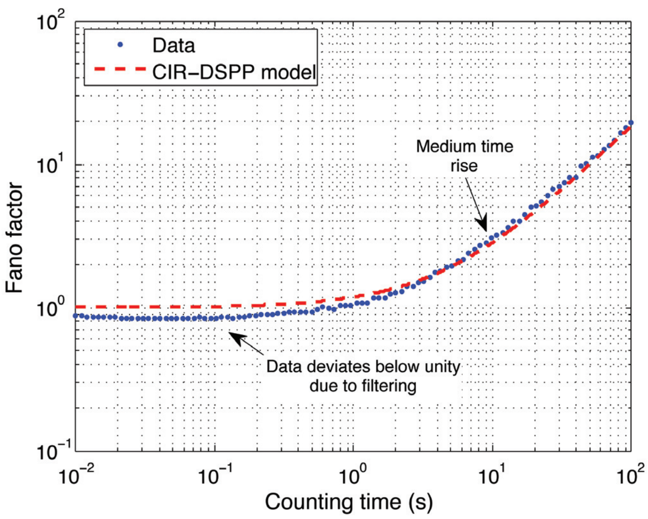


Fig. 11. Fano-factor time curve computed from filtered spike-train data (blue dot points). A doubly stochastic Poisson model (red dashed line) can describe clustering characteristics of the curve for counting times between 1 and 100 seconds. Deviation between the model and observation at counting times less than 1 second are introduced by the filtering operation.

Long time clustering of the snapping shrimp noise refers to time scales longer than 400 seconds, or greater than a few minutes. Fluctuations in the number of snaps that occur on these time scales are increasingly likely to be affected by environmental factors such as time of day or season. A recent simulation study (Legg & Chitre, 2012) has shown that diurnal variations can have a strong effect on the Fano-factor time curve and that observations of long-term clustering in snapping shrimp noise are most likely caused by these diurnal fluctuations. The measurement requirements to confirm these results using real shrimp noise are very substantial; however we are planning to make these measurements as part of future research efforts.

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