Ambient noise forward prediction from measured characteristics and high resolution modeling

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ABSTRACT

An analysis of temporal statistics of ocean ambient noise level time series data is used to determine basic characteristics such as the coherence time of noise level, the frequency distribution and spectrum of noise level fluctuations, and the expected duration of noise excursions from the mean. Conclusions are drawn from this analysis about the effective design of noise surveys and about noise exposure times to marine mammals. Simple formulas are presented to describe forward projection of noise levels in the near term future based on first- and second-order Markovian processes. In addition detailed propagation modeling of the noise from discrete shipping, coupled with appropriate source motion models, is used to support noise forward prediction.

Keywords: Ambient Noise, Fluctuations, Markov I-INCE Classification of Subjects Number(s): 56.3

1. INTRODUCTION

An analysis is presented of several statistical parameters derived from ocean ambient noise data that go beyond the usual collection of averages and variances. Emphasis is placed on temporal statistics that can be used to predict such parameters as expected waiting times before a certain threshold is crossed, or expected noise level at some time in the near future.

2. REPRESENTATIVE OMNI-DIRECTIONAL NOISE DATA

2.1 Sample Time Series of Omni-Directional Noise Level.

Several sets of long term ambient noise data, both omnidirectional and beam noise, measured from fixed sensors and from towed sensor arrays, were examined in order to identify stable and meaningful statistical parameters for data basing purposes. A representative example of omnidirectional ambient noise, lasting about one month, is shown in Figure 1. This figure shows a time series of one-third-octave band noise spectrum level at 50 Hz in the Pacific Ocean near California. This time series is representative of what is seen at other locations as well.

The figure also shows a histogram of the data, oriented on its side, in contrast to the customary way histograms are presented, in order to align more informatively with the time series.

2.2 Fitting Measured Histogram with Analytical pdf.

It is common within the application community to consider the probability density function (*pdf*) of noise levels as Gaussian, which would be characterized by an average level and a standard deviation. We see from the histogram in Figure 1 that the general character of the distribution is consistent with a Gaussian representation, and we see, also, that a more accurate description of the pdf would be to include some measure of asymmetry, such as the skewness. The values of these parameters for the example in Figure 1 are: average level (computed in dB) = 90.80 dB, standard deviation = 4.73 dB, and skewness = 1.25.

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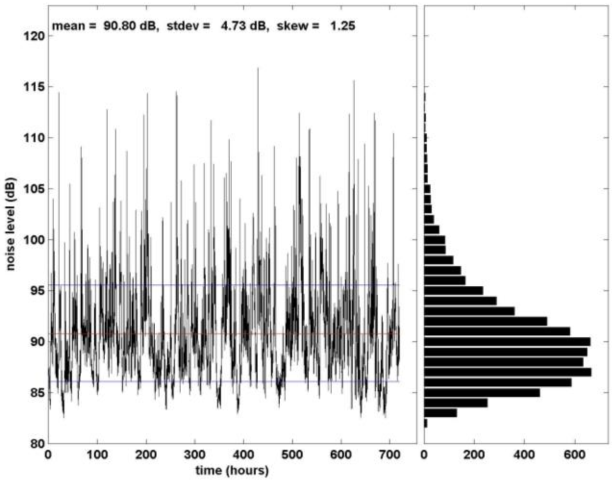

Figure 1 − One-third-octave-band omnidirectional ambient noise at 50 Hz near California coast.

3. TEMPORAL PROPERTIES OF NOISE

3.1 Coherence Function and Coherence Time

Analysis of the data time series provides several measures that define the temporal charter of noise, as illustrated in Figure 2. The black curve in the left hand panel is the temporal coherence function computed from the time series as a function of time shift in hours. The estimated coherence time of 1.75 hours for this time series is defined as that time where the black curve crosses the 1/e value, approximately 0.368, indicated by the horizontal green line. The temporal coherence function is a measure of the similarity of a time series to a time-shifted replica of itself. The red curve is the theoretical temporal coherence function, which is explained later.

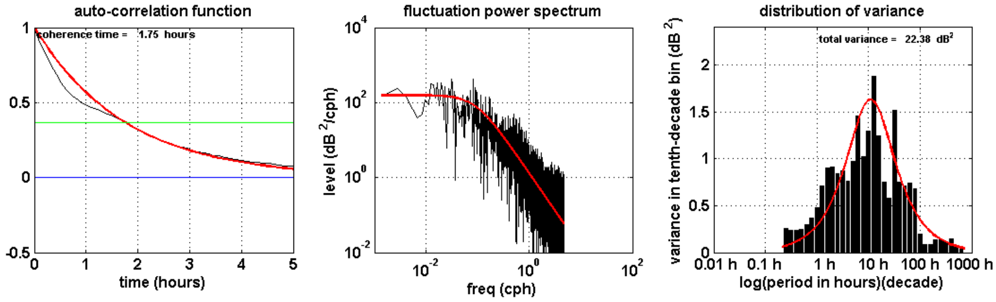

Figure 2 − Temporal dynamics of omnidirectional noise, comparison to first-order process.

3.2 The Fluctuation Power Spectral Density

The black curve in the central panel is the computed power spectral density, Φ, of the fluctuations in noise level about its mean value. As is customary, the PSD is presented on a log-log scale, and the red curve is the corresponding theoretical result for a first-order Markov process, explained later. Each plotted value represents the fluctuation power in uniformly sized bins of 1 cycle per hour (cph) each. The symbol Φ used here represents the two-sided power spectral density defined from $-\infty$ to $+\infty$.

3.3 The Logarithmic Power Spectrum

In some applications it is more informative to show the fluctuation power in proportional, rather than uniform, frequency bins. This can be achieved by forming the logarithmic power spectrum,

$$\Psi(f) = 2f\Phi(f) \quad , \tag{1}$$

defined for positive f, and represented by the bar graph in the right hand panel, plotted on a logarithmic scale of period, rather than frequency. The bar graph indicates how the noise level time series variability is distributed in time period. The choice to plot against time period rather than frequency is a deliberate one, done in order to express the results in a way thought to be more meaningful to the user.

Each plotted bar gives the contribution to the variance about the mean in a tenth-decade bin, centered at the indicated period. The total power in the fluctuation spectrum is the variance σ^2, equal to 22.38 dB^2, which may be calculated from the logarithmic spectrum. The sum of the bars is the total variance. The red curve is the corresponding theoretical curve for a first-order Markov process. Its peak occurs at a period related to coherence time τ_c by $T_{max} = 2\pi\tau_c$. We see from this panel that most of the variability, when viewed in proportional bands, occurs at periods bracketed by roughly about 2 to 20 hours. Understanding the time scales involved in the fluctuating noise levels is an important first step to developing meaningful noise survey designs and evaluating marine mammal harassment restrictions.

3.4 Markov Process Models

The observed random fluctuations of noise level about the mean show properties that are similar in some respects to those of first- and in some cases second-order Markov processes. A defining characteristic of a first-order Markov process is its theoretical exponential coherence function $\varphi = \exp(-\mu t)$, where μ is the inverse of the coherence time. This expression is used to compute the red line theoretical result in the left panel of Figure 2, using the inverse of the measured coherence time $1/\tau_c$ as the value of μ.

One finds also the following theoretical expressions for the power spectral density

$$\Phi(f) = \frac{2\mu\sigma^2}{\mu^2 + (2\pi f)^2} \quad , \tag{2}$$

and for the logarithmic power spectrum

$$\Psi = \frac{4\mu f\sigma^2}{\mu^2 + (2\pi f)^2} \quad , \tag{3}$$

both of which are used to plot the red theoretical curves in the central and right panels of Figure 2. A similar set of equations can be written for the second-order Markov process.

3.5 Forward Projection of Noise Level

One possible use of Markov process models is to forecast noise values into the near future. A first-order process may be written in a recursive form as

$$n_p(t + \tau) = e^{-\mu\tau} n(t) \ , \tag{4}$$

which can then be used to predict, or forecast, the noise n_p at time $t + \tau$, based on its observed value at time t. The corresponding expected mean square error in the prediction for the first-order process is $mse = \sigma^2 [1 - \exp(-2\mu\tau)]$.

Figure 3 illustrates the prediction errors that result when attempting to forecast the noise time series of Figure 1 by four different algorithms: using the present value for all future predictions, using the long term mean value, using the recursive first-order prediction formula based on the measured coherence time, and using a corresponding prediction formula for a second-order process. For this example, the first-order predictor gives the least error, and the second-order predictor gives serious overshoot. Examples have been seen, however, where the noise process more closely resembles a second-order process, and for these cases the second-order predictor gives the best results, as measured by the least rms error.

Viewing the noise as a Markov processes in this analysis is a step to provide short-term ambient noise estimates when only a few basic statistical parameters are available, based on recent in-situ measurements or possibly drawn from archival data as well.

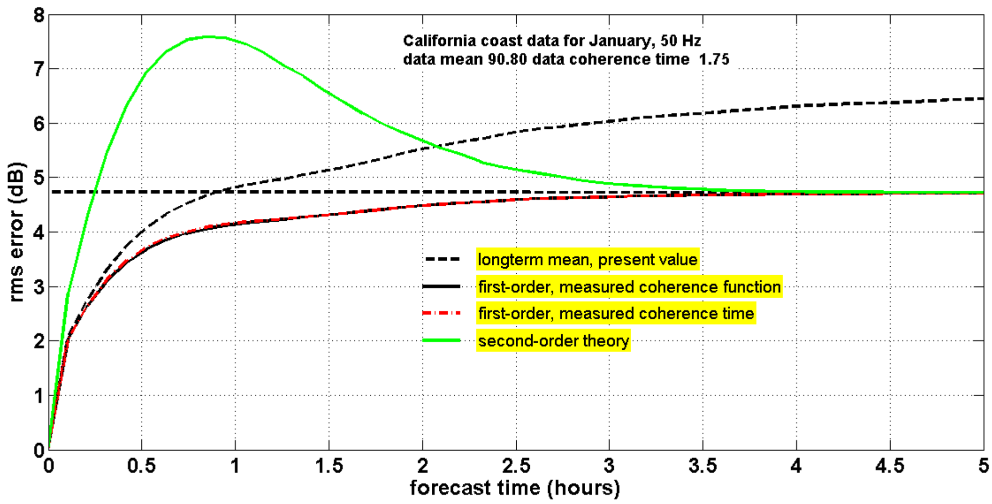

Figure 3 − Comparison of prediction errors against forecast time.

3.6 Distribution of Threshold Crossing Runs

Another application of noise temporal properties is to ascertain how often the noise level rises above, or drops below, a specified threshold level, and for what duration does this condition persist. For example, Figure 4 presents the expected number of times, normalized to 1000 consecutive noise samples, that a run or sequence of observations will lie below a threshold value of 85.8 dB, based on the noise time series in Figure 1. The square data symbols are based on the actual data.

The probability of having a noise sample below the stated threshold, as determined from the data, is $p = 0.108$, and from elementary probability theory for independent observations, the probability that, given an initial observation below threshold, the next n-1 observations will also lie below threshold, followed by an above threshold observation, is $P_n = p^{n-1} (1-p)$, indicated by the red line in Figure 4.

Consecutive noise samples in Figure 1, however, are not independent, and the governing probability needed is the conditional probability that, given an observation below threshold, the next observation will also lie below the stated threshold. That conditional probability in this case is 0.721. Using this value one obtains the black line in the figure. The black line better represents the actual run lengths computed directly from the data.

3.7 Simulations of Shipping Noise

A time series of simulated shipping noise was generated through the combined use of shipping noise source models, range dependent propagation models, and vehicle motion simulation models for the location and time period corresponding to the data in Figure 1. Attention is addressed here to the temporal variability of the simulated process, as displayed by the distribution of variance results in Figure 5. Comparing this result to the corresponding data-based result in the right panel of Figure 2, one finds that the observed variance is approximately twice the simulation variance, and the simulation bar graph shows two peak regions with a pronounced hole near the period of 10 hours. The red curve is the theoretical result for a first order process based on the simulated values. These results cast doubt on the validity of using simulated noise, by this approach, as a representation of data.

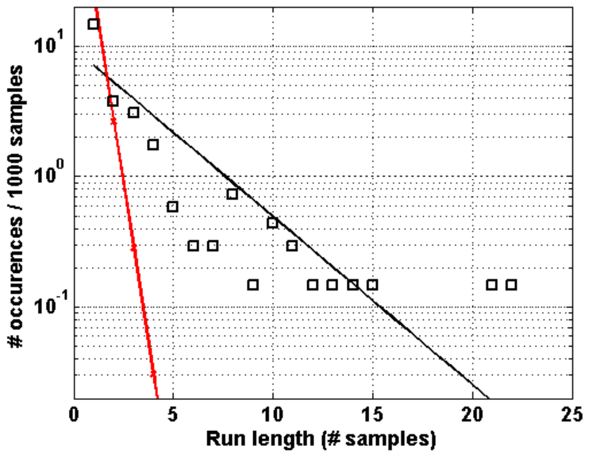

Figure 4 − Distribution of run lengths below 85.8 dB for series in Figure 1

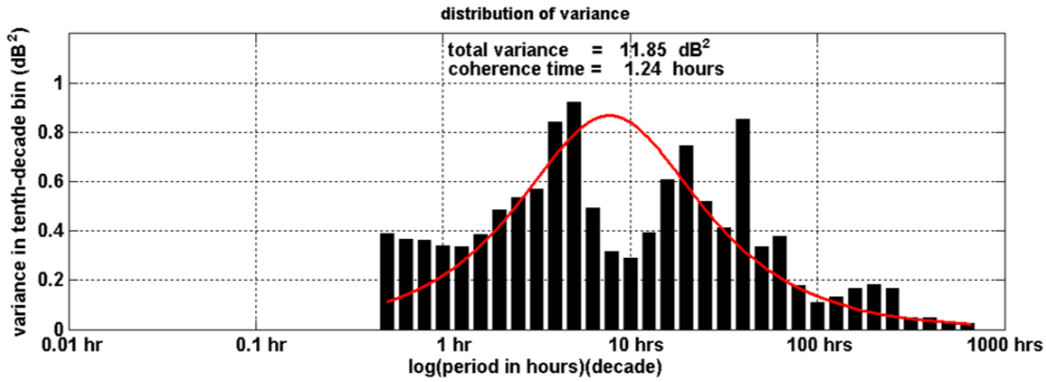

Figure 5 − Distribution of Variance for simulated shipping noise.