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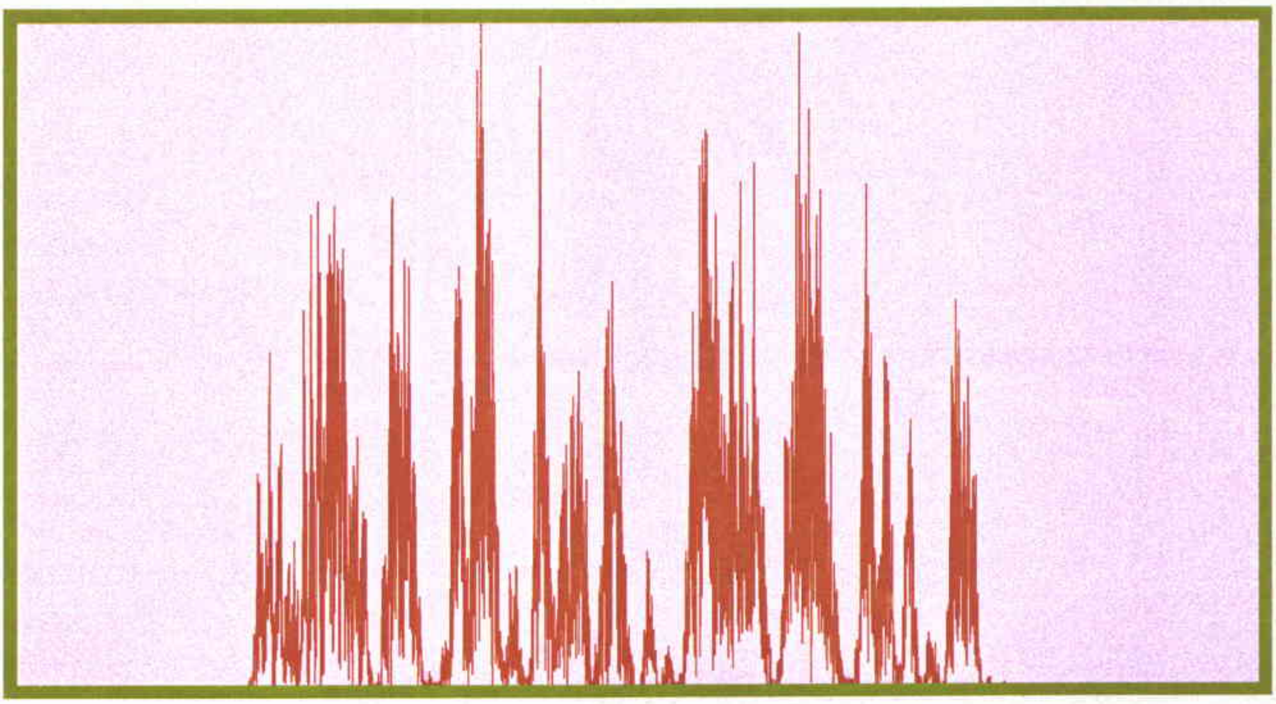
Predicting underwater ambient noise with an evolutionary signal processing method



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Predicting underwater ambient noise with an evolutionary signal processing method

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Predicting underwater ambient noise with an evolutionary signal processing method

Alberto Alvarez, Chris Harrison, Martin Siderius

Executive Summary:

The technique contained in this report could improve passive sonar detection and classification capabilities by predicting ocean ambient noise. Specifically, a novel processing method in the time domain for the analysis of the ocean ambient noise predictability is presented. The approach is based on recent progress in non-linear physics and artificial intelligence involving evolutionary computation. The method extracts the deterministic part of a given sound record and provides an analytical functional form that describes the deterministic variability of the record. This functional relation is employed to predict future values of ocean noise amplitude. The processing approach has been succesfully tested. The results obtained indicate that the proposed technique could also improve underwater communications and active sonar detection.

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Predicting underwater ambient noise with an evolutionary signal processing method

Alberto Alvarez, Chris Harrison, Martin Siderius

Abstract:

In this report we employ recent developments in non-linear physics and time series prediction to study the physical characteristics of measured underwater ambient sounds. Specifically, we examine the predictability of a sample of ocean ambient noise recorded in the Strait of Sicily, Italy. An approach based on genetic algorithms has been employed. Results indicate that, while showing complex time variability, the recorded signals are highly predictable.
Keywords: Underwater ambient noise ○ evolutionary computation ○ predictability

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1 Introduction

Until recently, complex phenomena were considered to result from complicated physics among many degrees of freedom. In these situations, dynamical models describing these phenomena cannot usually be derived from first physical principles. Instead, an estimation of the dynamics can be obtained directly from observations of the system evolution. Traditionally, such estimation is obtained assuming that the observed time series generated by the system evolution, is produced by a linear system excited by Gaussian noise [1]. The variability of the time series is then assigned to the stochastic nature of the excitation, which cannot be modelled.

Nowadays, it is well known that apparent randomness and complex phenomena can be due to the chaotic nature of nonlinear but deterministic dynamics involving only a few degrees of freedom. In such cases, it is possible to model the characteristics of the system deterministically, obtaining short-term predictions of the system evolution more accurate than those obtained from a linear stochastic model. Specifically, the works of Takens [2], Casdagli [3], and others (for review see [4, 5]) have established the methodology for building a dynamical model from a chaotic time series. In their approach, the time series $\{x(t_i)\}, i = 1 \cdots N$ describing the system evolution is considered as the output of a deterministic, nonlinear autonomous dynamical system:

$$\frac{d\vec{s}}{dt} = \Phi\left(\vec{s}\right) \tag{1}$$

where $\vec{s}$ is a K-dimensional state and $\Phi(\cdot)$ is a nonlinear vector field. A scalar-valued measurement function $h(\cdot)$ relates the dynamical system Eq. (1) with the measured variable $x(t) = h(\vec{s})$. When working with experimental data, we generally do not know the state equation Eq. (1) but we are restricted to observed the outputs of the dynamical system. A fundamental issue is what can be inferred as to the dynamics Eq. (1) from the observation of the output time series $\{x(t_i)\}, i = 1 \cdots N$. Takens [2] proved that the use of a sampled observable $x(t)$ of the dynamical system and its delayed versions:

$$\vec{\mathbf{x}}(t) = [x(t), x(t-\tau), \cdots, x(t-(m-1)\tau)] \tag{2}$$

with τ a delay and m larger than 2 d_e (with d_e the dimension of the attractor, i.e., the geometric object created by the trajectories after the transient died out), provides m-dimensional space that is a proxy for the full multivariate state space of the system Eq. (1). In more mathematical terms, this statement means that there is a one-to-one smooth map Ψ with a smooth inverse from the K-dimensional state space of the original system to the Euclidean reconstruction space R^m. Such mapping is called embedding and the theorem is known as the Takens Embedding Theorem. The embedding theorem guarantees that the system's state information can be recovered from a sufficiently long observation of the output time series. According to the theorem, it also follows the existence of a smooth map $P : R^m \to R$ satisfying:

$$x(t) = P(x(t-\tau), x(t-2\tau), \cdots, x(t-m\tau)). \tag{3}$$

Thus, building a dynamical model from a time series implies a two-step process. The first step is to use the inmediate past of the time series to reconstruct the current state of the system (state space reconstruction), with time delay embedding Eq. (2), where the dimension d_e of the attractor is estimated by the correlation dimension algorithm [6] and the time delay τ can be fixed by different methods [7]. The second step is to build the predictive model $P(\cdot)$ of (3). During the past decade, various techniques have been developed to accomplish the task of approximating the mapping $P(\cdot)$ defined in Eq. (3). These techniques can be classified in two groups: local and global dynamical models [8]. The local dynamical methodologies divide the state space of the system, reconstructed from the time series, in local regions to model individually the local dynamics in each region. The total dynamic model is then obtained by piecing together all the local models. An example of these local dynamical models is the method of "nearest neighbours" from chaos theory. On the other hand, global models have been the most explored for time series predictions. Examples of these global models are based on polynomial fitting, neural networks and radial basis functions among others. Other global procedure based on the Darwinian theories of natural selection and survival are emerging [9]. These procedures, called evolutionary algorithms, have already shown to be robust approaches to determine the functional form for $P(\cdot)$ [10]. The main advantages of this method is that sparse data are sufficient and, as a byproduct, these algorithms can indicate the analytical functional form that underlies the signal.

Time series of ocean ambient sounds show complex variability. Underwater background sound is caused by a large number of physical, biological and anthropogenic elements. The range of sources contributing to the underwater sound has lead to consideration of the phenomena as random "noise" that was unpredictable and uncontrolled. However, recent studies have found that the complex time-variability of ocean ambient sounds may be described by the chaotic nature of a nonlinear and deterministic dynamic involving only few degrees of freedom [11]. This result addresses the possible prediction of underwater ambient noise in the short term. This limited predictability could be used for purposes of enhancing underwater signal detection, source localization and classification.

The report attempts to examine the level of predictability of ambient background acoustic data collected in different scenarios. This task has been achieved by developing a novel signal processing and prediction method that merges recent techniques from statistics, non-linear physics and artificial intelligence [12]. Our motivation is to establish the basis for future time domain noise mitigation strategies to enhance underwater signal detection, source localization and classification.

2
Data

Underwater ambient noise samples were recorded during the experiment ADVENT99 in the Strait of Sicily, Italy, in Spring 1999 (Fig. 1). Ambient noise signals were received on a vertical array of hydrophones that spanned 62 m of the 80 m water column. The hydrophone array was bottom moored and mantained vertical position using a sub-surface float. The acoustic data was transmitted to the research vessel *R/V Alliance* by radio telemetry. Ambient noise data from the array was collected in the band 10 – 2000 Hz with a sampling frequency of 6000 Hz.

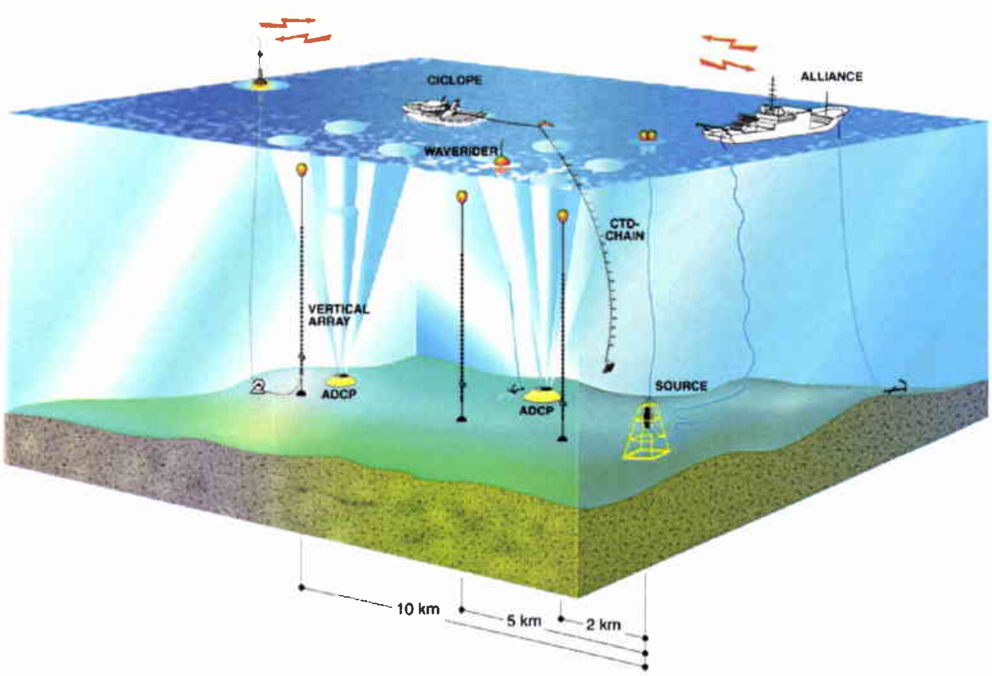

Figure 1 *Scenario of the field experiment ADVENT99.*

3
The evolutionary processing-prediction method

Given an underwater ambient sound record, the goal of our evolutionary processing approach is to find the empirical map $P(\cdot)$ of Eq. (3) describing the time variability of the recorded sound. The existence of the map $P(\cdot)$ is guaranteed by Takens' theorem only for deterministic time-series. However, it would be expected in principle that the observed variability of any experimental time-series will consist of a deterministic (predictable) and a truly random (unpredictable) part. Noisy data leads to worse performance of any predictor system. This is because the system attempts to predict the noise (i.e., find a dynamical law of a random effect) at the expense of predicting the true underlying dynamics. In consequence, some filtering, to isolate the deterministic variability in the data from that of purely stochastic nature, should be applied to the record before attempting to find the map $P(\cdot)$.

A widely employed time-domain technique to remove the stochastic part of the time variability of the signal, without losing a significant portion of its deterministic nature is Singular Value Decomposition (SVD) [13]. Briefly, the lagged-covariance matrix of the record is computed and diagonalized and the eigenvalues are ranked in descending order. These eigenvalues are the average root-mean-square projection of the delay coordinate time series on to the eigenvectors (called empirical orthogonal functions or EOFs) that define a new coordinate system, which is a rotation of the original delay coordinate system. To resolve which eigenvalues represent a predictable variability, a nonlinear prediction approach has been employed [14]. Essentially, the signal to be filtered is rebuilt using only a certain number of biggest eingenvalues obtained from the SVD decomposition. Then, a nonlinear prediction method is employed to analyse the predictability of the reconstructed time series. If the forecast performance of the nonlinear predictor is high the reconstructed signal is considered mainly deterministic. A new time series is rebuilt from the original one considering a greater number of eingenvalues and the process is repeated. The procedure is ended when the inclusion of new eingenvalues degrades the forecast skill. At that point, it can be argued that the variability represented by the new eingenvalues has a strong noisy component. The final filtered signal is rebuilt from the original with the maximum number of eingenvalues providing a good forecast skill from the nonlinear predictor, in our case, a genetic algorithm.

A genetic algorithm has been employed, in order to approximate the functional form $P(\cdot)$ in Eq. (3). Briefly, to find a near-optimal solution to Eq. (3), the genetic algorithm proceeds as follows (for details see [10]), Fig. 2: Given a time series, $\{x(t_i)\}, i = 1 \cdots N$, a set of candidate equations (the population) for $P(\cdot)$ is randomly generated. These equations (individuals) are of the form of Eq. (3) and their right hand sides are stored in the computer as sets of character strings that contain random sequences of the variable at previous times ($x(t-\tau), x(t-2\tau), ..., x(t-m\tau)$, with τ the time delay parameter), the four basic arithmetic symbols ($+,-,\times$, and $/$), and real-number constants. A criterion that measures how well the equation strings perform on a training set of the data is its fitness to the data defined by:

$$R_g^2 = 1 - \frac{\Theta^2}{\sigma} \tag{4}$$

where σ represents the total variance of the data and Θ is given by:

$$\Theta^2 = \sum_{t=m+1}^{N} \left(x(t) - P\left(x(t-\tau), x(t-2\tau), \cdots, x(t-m\tau)\right)\right)^2 \tag{5}$$

R_g^2 measures the percentage of the time series variance that is explained by the predicted field. Values of R_g^2 close to one represent high accurate predictions, while low positive or negative values indicate poor forecast capability. The equation strings with highest values of R_g^2, are selected to replace parts of the character strings between them (reproduction and crossover) while the individuals less fitted to the data are discarded. A small percentage of the equation strings' most basic elements, single operators and variables, are mutated randomly. The process is repeated a large number of times to improve the fitness of the evolving population.

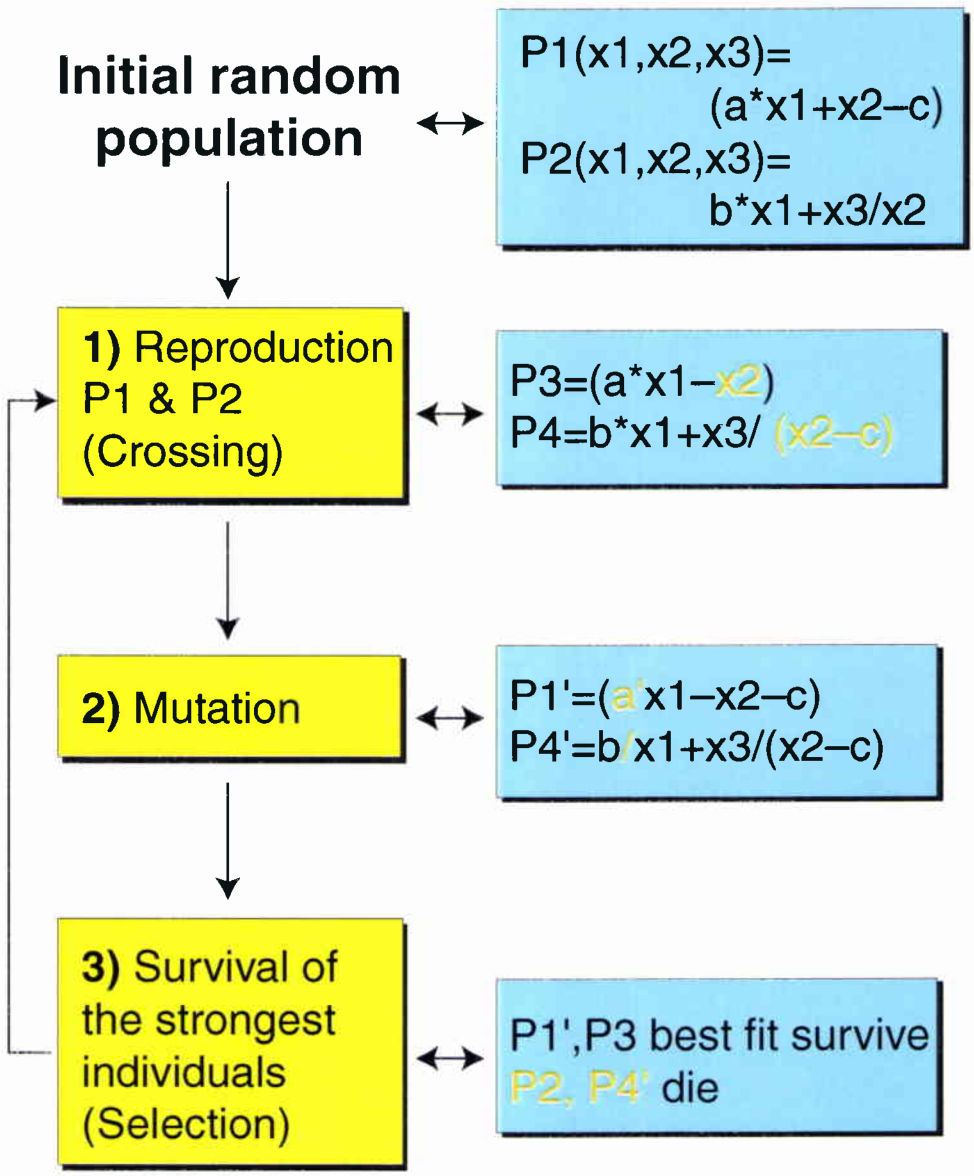

Figure 2 *Flow chart of the genetic algorithm* $(xj \equiv x(t - j\tau))$

4

Results

The processing method was applied to a sample of 5 s (30000 points) of the data recorded at 30 m depth (hydrophone 32) in different ambient noise situations. The first 0.16 s of each signal (first 1000 points) were subjected to the SVD analysis, with a windowing of 0.05 s (300 points), in order to determine the basis of eigenvectors describing the statistical properties of the time series. The first 0.04 s (250 points) are used by a genetic algorithm to find the maximum number of eigenvectors that reconstruct a deterministic time series and the deterministic law underlying the reconstructed signal. Specifically, the genetic algorithm is trained using the first 200 points while the remaining $N = 50$ points are used to compute the forecast skill R_g^2. The minimum threshold to consider the reconstructed time series deterministic, is $R_g^2 = 0.95$.

A second set of the total sample is considered in order to validate the deterministic nature described by the computed eigenfunction basis and functional relation Eq. (3). This validation set ranges from 2.5 to 5 s (15000 samples). More specifically, the validation test proceeds as follows: A reconstructed time series of the validation set,$\{x'(t_i)\}, i = 1 \cdots N_v$ (being N_v the total number of points in the validation set), is computed employing the previously selected eigenfunction basis. The part of the total variance of the signal that is predictable is defined by:

$$R^2 = R_g^2 \left(1 - \frac{\sum_{t=1}^{N_v}(x(t) - x'(t))^2}{\sum_{t=1}^{N_v}(x(t) - \bar{x})^2}\right) \tag{6}$$

where $\bar{x}$ is the mean value of the time series in the validation set and $x'(t)$ is the reconstructed time series considered as deterministic. Notice that R^2 is constituted by two factors: one describing the part of the total variance represented by the reconstructed signal obtained by the SVD and the second, R_g^2 that indicates which part of the total variance of the reconstructed signal is predicted by the functional relation Eq. (3) found by the genetic algorithm.

High predictability should still be expected if the EOF basis as well as Eq. (3) truly describes deterministic nature. On the other hand, if the sample is dominated by noise, the previously computed statistics and predictor will not be representative of the variability of the validation set. In this case, poor predictability should be obtained. The rate of the total variance of the validation set, that can be explained and predicted by a deterministic nonlinear model is represented by:

The evolutionary algorithm built to find the mapping P in Eq. (3) for each situation was configured in such a way that the value of the parameter m is $m = 8$, τ equals to the discrete time unit $\Delta\ t$ ($\equiv 1.66\ 10^{-4}\ s$) and the maximum number of symbols allowed for each tentative equation is 20. Each generation consists of a population of 120 randomly generated equations. A total of 10000 generations was considered for each case.

4.1 Dominant ship noise environment

Figure 3a shows a 5 s acoustic signal recorded by hydrophone 32 when a ship was moving near the array. Due to the proximity of the ship it can be inferred that the recorded signal is mostly dominated by ship noise. While showing complex time variability, ship noise is highly correlated and predictable. Supporting this hypothesis, Fig. 3b shows that the recorded underwater signal can be predicted with 85% of accuracy in the first 0.04 seconds. Specifically, the red line represents the filtered signal reconstructed from the original (blue line) and a forecast skill of $R_g^2 = 0.95$. The reconstructed signal accounts for almost 90% of the total variance. The dynamical law found by the genetic approach is given by the expression:

$$x(t) = 1.52\ x(t - \Delta t) - \frac{(x(t - 2\Delta t) + x(t - 3\Delta t) - 1.4\ x(t - 5\Delta t) + x(t - 6\Delta t))}{1.9} \tag{7}$$

where $x(t)$ is the signal amplitude and $\Delta t = 1.66\ 10^{-4}\ s$. Figure 3c shows the rate of the total variance of the validation set, that can be explained and predicted by a deterministic nonlinear model. Specifically, it is found that the underwater signal constituting the validation set can be predicted using the proposed approach with 82% of accuracy. The slightly lower predictability than in the first set of data 2.5 s earlier, indicates the stationary deterministic nature of the signal, well represented by the previously extracted EOFs and functionally characterized by the relation Eq. (7). Finally, Fig.4 shows the existence of a band structure of the predictable signal confirming its shipping origin.

4.2 Dominant wind noise environment

A beamforming technique was employed on the hydrophone array to extract the sound signals from the upwards direction, i. e. the sea surface. Because of the beam's frequency-dependent angular resolution, the dominant noise source is wind at high frequencies, but noise from distant ships may still be present at low frequencies. Figure 5a shows the breaking wave sounds generated by the wind. The procedure described in the previous ship noise dominant case was also applied to this record. The beamformed signal can be almost totally predicted as shown in Figs 5b and c. A simple prediction law found by the evolutionary program is given by:

$$x(t) = 0.24\ x(t-\Delta t) - 0.75\ x(t-2\Delta t). \tag{8}$$

In principle, such high predictability would not be expected from processes generated by more or less random sources such as wind forcings. In fact, this high forecast skill derives from the fact that most of the variability of the beamformed signal is at very low frequencies. Low frequency variability is more predictable over short intervals than high frequency variability. In consequence, the high predictability of this example is induced partially by the filtering effect of the beamforming process.

4.3 Dominant mechanical noise environment

The recorded data show intermittent corruption by mechanical noise probably produced by the hydrophone hitting the array hose in a heavey sea, Figure 6a. We have chosen the first of these events to extract the statistics characteristic of the process and the prediction function as previously described. It has been found that the functional form:

$$x(t) = x(t-\Delta t) - \frac{(-0.04\ x(t-4\Delta t)\,(x(t-3\Delta t)-3.86) + x(t-5\Delta t) - x(t-3\Delta t))}{x(t-3\Delta t) - (x(t-7\Delta t) - 2.26)} \tag{9}$$

predicts the noise episodes with 90% of accuracy. This can be easily inferred from Fig. 6c where high predictability is obtained when the banging events are present in the sound record.

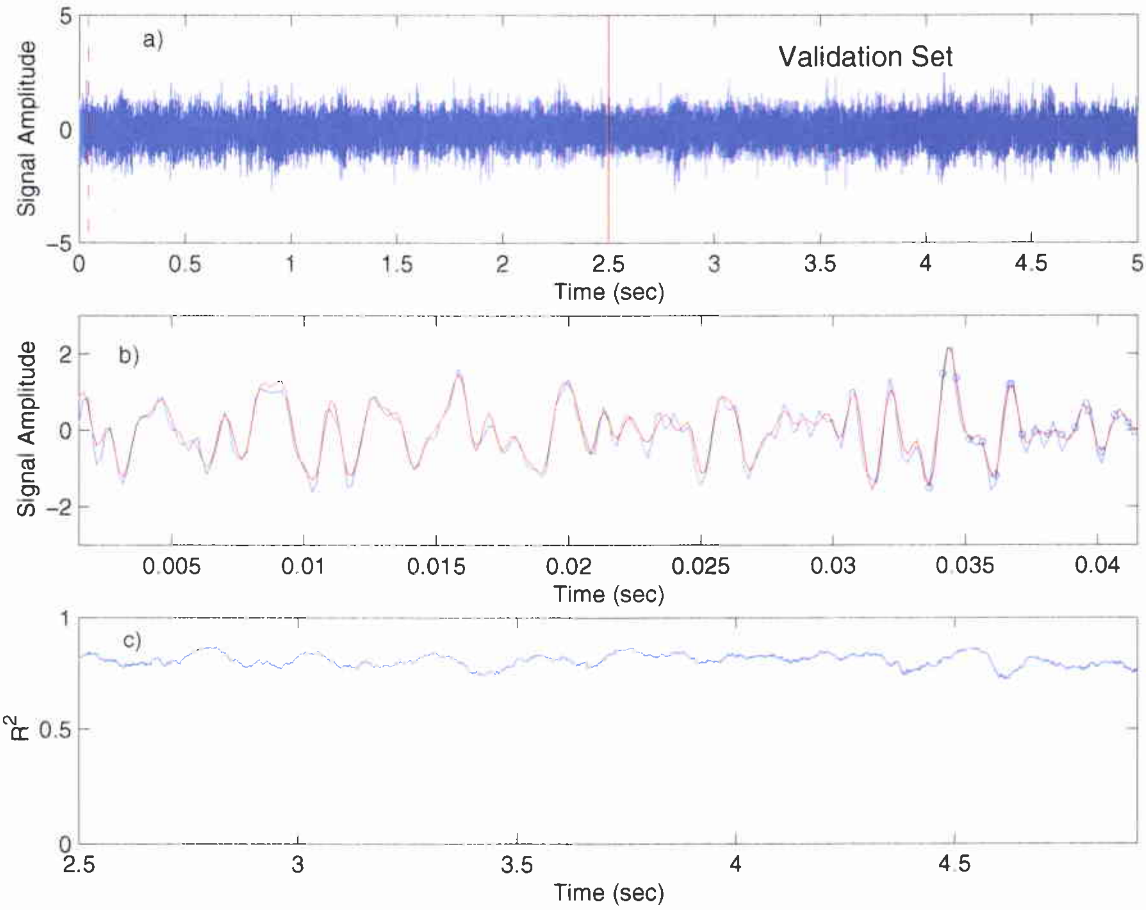

Figure 3 *a) Ship noise recorded by the hydrophone (blue-solid line). The red vertical lines indicate the datasets. Data from the initial point to the dotted line was used to extract the statistical properties of the signal. The data betwwen the initial point and the dashed-dotted line were used to extract the dynamical law. The validation set is between the solid line and the last point. b) Real data (blue) and forecasts (red) of the achieved dynamical law. c) Predictability in the validation set.*

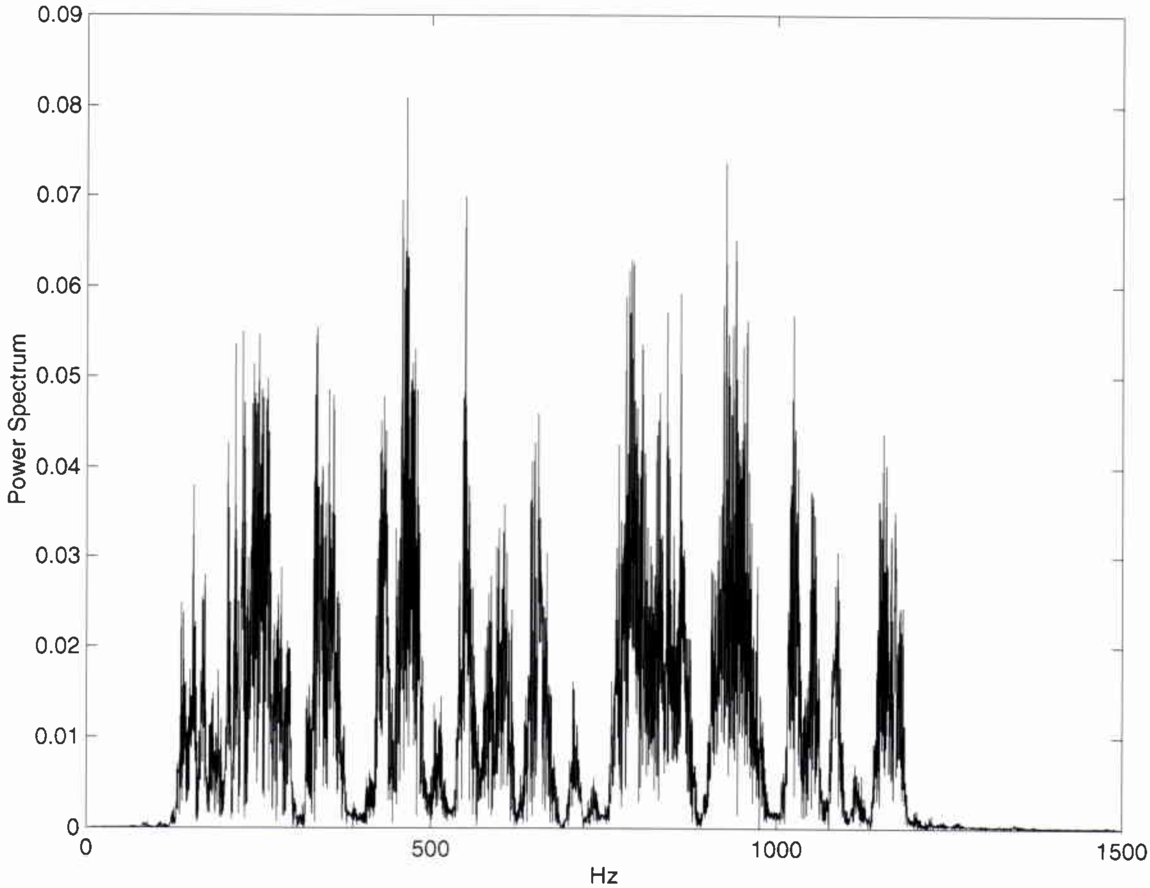

Figure 4 *Power spectrum of the deterministic signal in the case of a dominant ship noise environment.*

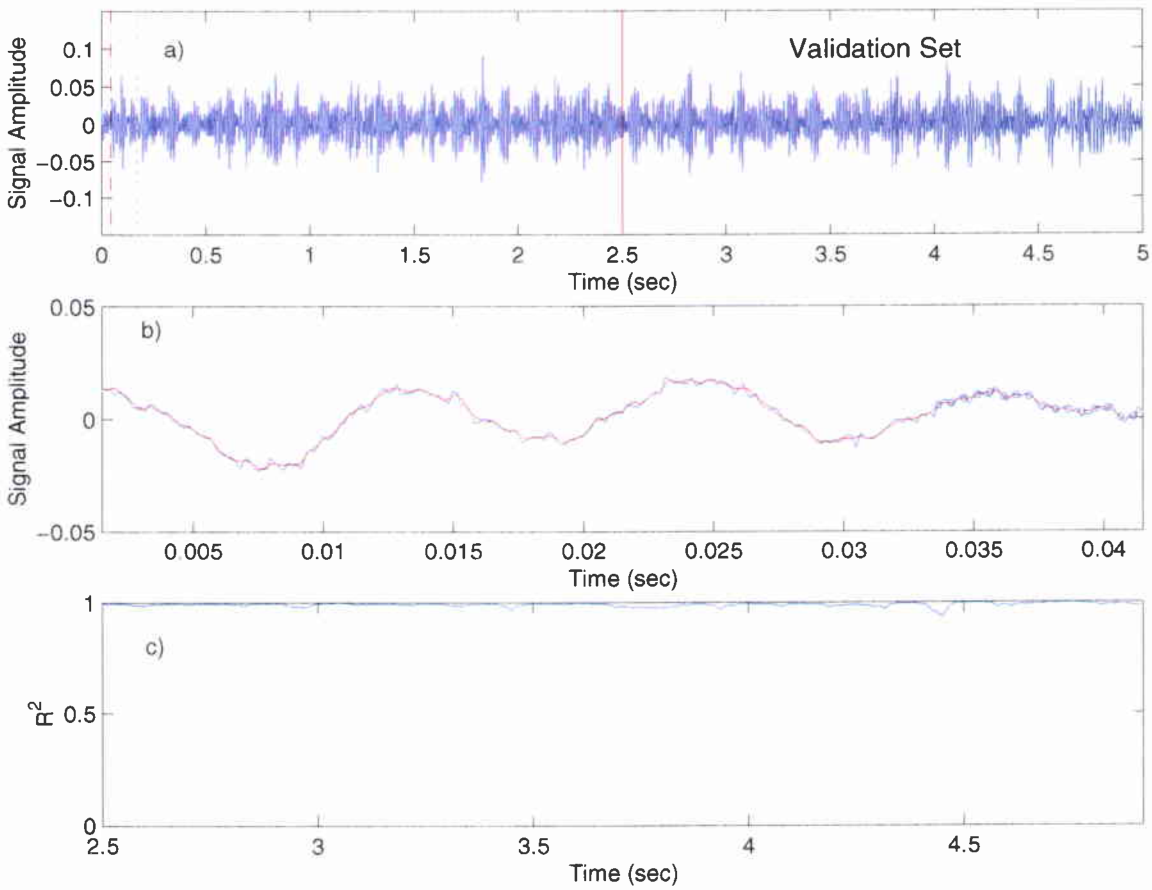

Figure 5 *a) Wind noise recorded by the hydrophone (blue-solid line). The red vertical lines indicate the datasets. Data from the initial point to the dotted line was used to extract the statistical properties of the signal. The data between the initial point and the dashed-dotted line were used to extract the dynamical law. The validation set is between the solid line and the last point. b) Real data (blue) and forecasts (red) of the achieved dynamical law. c) Predictability in the validation set.*

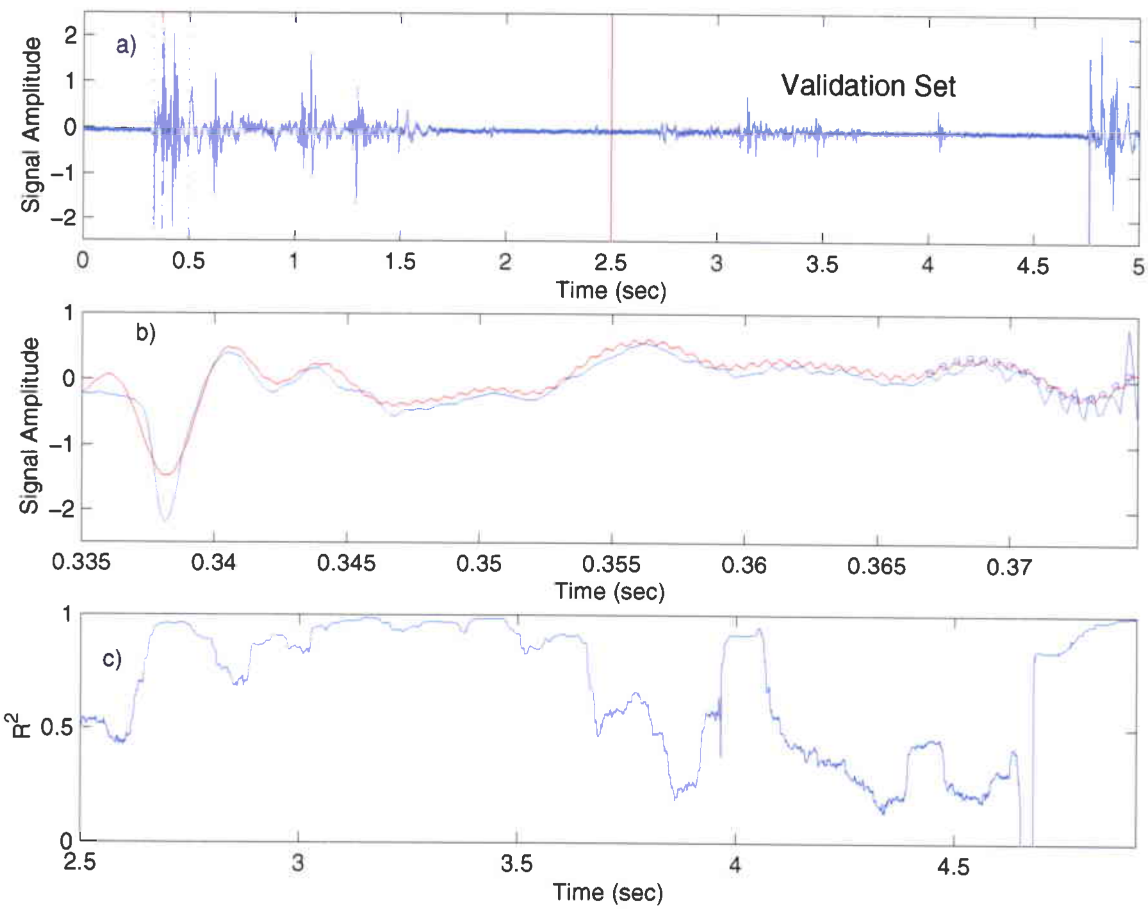

Figure 6 *a) Mechanical noise recorded by the hydrophone (blue-solid line). The red vertical lines indicate the datasets. Data from the initial point to the dotted line was used to extract the statistical properties of the signal. The data between the initial point and the dashed-dotted line were used to extract the dynamical law. The validation set is between the solid line and the last point. b) Real data (blue) and forecasts (red) of the achieved dynamical law. c) Predictability in the validation set.*

5 Conclusions

Recent developments in non-linear physics were applied to analysis of the predictability of underwater ambient noise. Results indicate that ambient ocean noise may be highly predictable allowing derivation of approximate dynamical laws of time variability. Future work will consider the applicability of this approach to develop underwater noise mitigation strategies in the time domain.

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Keywords

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