EXPERIMENTAL EVIDENCES FOR CHAOTIC DYNAMICS IN THE VOCALIZATIONS OF THE HUMPBACK WHALE *MEGAPTERA NOVAEANGLIAE*

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ABSTRACT

Vocalizations of the humpback whale *Megaptera novaeangliae* were investigated using the methods of the nonlinear time series analysis. Results show that the sound emissions are characterized by a combination of regular and irregular dynamic behaviors, the latter were characterized in terms of the maximum Lyapunov exponent and the Kaplan–Yorke dimension, while by the computation of the Lyapunov spectrum, a hyperchaotic attractor was found.

Keywords: nonlinear phenomena in animal vocalization, chaos, nonlinear time series analysis.

1 INTRODUCTION

The discovery of sound emissions from sea living organisms dates back to the pioneering studies of W.E. Schevill and B. Lawrence on the behavior of a group of beluga whales at the Saguenay River in Quebec in 1949 [1]. The interest evinced by biologists and zoologists rapidly led to systematic investigations on the production of sounds from sea living species, allowing for the identification of a variety of uttering behaviors [2]. Soon, vocalizations were recognized as an exclusive characteristic of whales, dolphins and porpoises – marine mammals belonging to the Cetacea taxonomic order [3]. The distinctive features of these sound emissions were proven to be strictly dependent on both social behaviors and environmental conditions [4]. Purposes other than communication, such as echolocation, were also pointed out by Norris and others [5, 6]. Owing to its unusual types of vocalization, great attention was devoted to the humpback whale *Megaptera novaeangliae* (Borowski, 1781), a mysticete belonging to the family Balaenopteridae which is characterized by highly complex social behaviors [3]. The name itself stems from the whale's acrobatic breaches, performed with an arching of its back, supposed to represent forms of visual and acoustic communication [7]. Unlike other species, this mysticete does not form stable social groups, but has just occasional brief associations during the seasonal migrations [8]. Their most interesting hunting strategies are based on underwater air exhalation the aim of which is to herd the prey at the surface [8]. Both individual and collective so-called 'bubble behaviors' are exhibited. In the latter case, large groups of whales, which may number nearly 20 individuals, dive down up to 30 m near a school of fish and scare the prey in moving towards the water surface by using a combination of sounds and movements. At the same time, while circling around the school, whales swim slowly to the surface along spiral paths constantly blowing bubbles that form a dense net entrapping the concentrated mass of prey and preventing any massive escape. Then, the individuals lunge up together keeping their mouths open in order to engulf large quantities of food. Careful observations of these hunting events have demonstrated the high level of cooperative tactics organization [8]. In the context of the same feeding session, bubble netting and subsequent emersion are guided by a single individual, generally a female, while the other whales always keep the same reciprocal disposition. All the movements seem to be coordinated by a continuous sound emission. An intense grumble accompanies bubble netting, while a sudden rise in pitch, the

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so-called 'ascending phrase', occurs just before the whales lunge for the surface [8]. The astonishing connection between sound emission and cooperative hunting has been considered as a valid support for the hypothesis on the existence of real communications among individuals. However, it represents just a single episode of vocalization among numerous others whose purpose is still unclear.

Humpback whales indeed produce a number of unusual sounds variously described as moans, groans, cries, squeaks and so forth [9]. Sounds are sometimes arranged into complex and predictable patterns classified as 'songs'. Songs consist of 'units', the shortest continuous sound detectable by human beings making up a 'phrase'. Phrases are variously repeated to create a 'theme' and themes, in turn, are combined to form a song. A typical song lasts for about from 7–30 min, with themes and phrases, respectively, from 1 to 3 min and from 20 to 30 s long. Sounds are characterized by frequencies ranging in the interval between 20 and 9000 Hz and intensity up to 185 dB [9]. Even if each whale has the capability of vocalizing, quite surprisingly only males are found to sing in the winter breeding grounds. Such a behavior has been generally related to mating or to forms of territorial display. Furthermore, the same song is repeated within a limited region and only small changes are detected during the same season. After the migration to polar feeding grounds and the return to tropical waters in the winter, songs appear extremely similar to the ones recorded at the end of the previous winter [8]. In spite of the large amount of research work, no clear explanation of the whole body of vocalizations has been found. Moreover, owing to the lack of information on the physiology of the respiratory apparatus during vocalization and the considerable experimental difficulties related to the behavioral observation in the wild, the dynamics of vocalization is still poorly understood. Nevertheless, indirect information could be inferred from a detailed study of sound patterns. In recent studies, nonlinear dynamics analysis was used to characterize vocal emissions of a different nature [10–13], and, in particular, chaos in other types of animal vocalization was characterized using the same method proposed here [14]. In this paper we perform a nonlinear time series analysis on the vocalizations of the *Megaptera novaeangliae*, looking for the signature of chaotic dynamics.

2 DATA ANALYSIS

Signals corresponding to different sound emissions, including moans, cries, whistles and songs, were considered. Attention was focused only on clearly discernible sound emissions to avoid any spurious effect due to echoes or noise. Fast Fourier transforms (512-point FFT) and spectrograms are used to perform a preliminary analysis looking for noise concentration patterns that are characteristic of nonlinear phenomena [15].

Nonlinear dynamics analyses were limited to signal units characterized by broadband features in the frequency domain. The results reported in the present work refer to a signal 10.7 s long, corresponding to 85,743 points, generally describable as a cry. Analysis methods were performed on a shorter unit of about 12,000 points, corresponding to a sound duration of 1.49 s. The investigation of the other signals, whose results are not shown for brevity, gave similar results.

3 NONLINEAR TIME SERIES ANALYSIS METHODS

The time evolution of a system can be properly measured by recording the time series. The time evolution of a system can be properly measured by recording the time series. The main task of nonlinear time series analysis is to extract information on the dynamical system starting from the observation of its evolution. This approach is basically different from the statistical one; it goes over the limits of the traditional linear and statistical approaches, considering the statistical processes as a special case of a larger class of phenomena. The analysis of the time series was performed using the software package TISEAN [16], valued as the most well known and robust algorithm set for nonlinear time series ana-lysis. Typical steps are attractor reconstruction from the time series and the characterization of the chaotic dynamic by means of Lyapunov exponents and the maximum Lyapunov exponent (MLE).

3.1 Attractor reconstruction

The attractor of the underlying dynamics was reconstructed in phase space by applying the time delay vector method [15, 17].

Starting from a time series $s(t) = [s_1, \ldots, s_N]$ the system dynamic can be reconstructed using the delay theorem by Takens and Mañe. The reconstructed trajectory **X** can be represented by a matrix where each row is a phase space vector:

$$\mathbf{X} = [X_1, X_2, \ldots, X_M]^T, \tag{1}$$

where $X_i = [s_i, s_{i+T}, \ldots, s_{i-(D_E-1)T}]$ and $M = N - (D_E - 1)T$.

The matrix has two key parameters: the *embedding dimension* D_E and the *delay time T*. The embedding dimension is the minimum dimension at which the reconstructed attractor can be considered completely unfolded and no overlapping is present in the reconstructed trajectories. If the chosen dimension is lower than D_E, the attractor is not completely unfolded and the underlying dynamics cannot be investigated. Higher dimensions are not advisable because of the increase in the computational effort.

The algorithm used for the computation of D_E is the method of *false nearest neighbors* [18]. A false neighbor is a point of trajectory intersection in a poorly reconstructed attractor. As the dimension increases, the attractor is unfolded with greater fidelity, and the number of false neighbors decreases to zero. The first dimension with no overlapping points is D_E.

The delay time T represents a measure of correlation existing between two consecutive components of D_E-dimensional vectors used in the trajectory reconstruction. Following a commonly applied methodology, the delay time T is chosen in correspondence to the first minimum of the average mutual information function [19].

3.2 Lyapunov exponents

Chaotic systems display a sensitive dependence on initial conditions. Such a property deeply affects the time evolution of trajectories starting from infinitesimally close initial conditions, and Lyapunov exponents are a measure of this dependence. These characteristic exponents give a coordinate independent measure of the local stability properties of a trajectory. If the trajectory evolves in a N-dimensional state space, there are N exponents arranged in decreasing order, referred to as the *spectrum of Lyapunov exponents* (SLE):

$$\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n. \tag{2}$$

Conceptually, these exponents are generalizations of eigenvalues used to characterize different types of equilibrium points. A trajectory is chaotic if there is at least one positive exponent, the value of this exponent, known as the *MLE*, gives a measure of the divergence rate of infinitesimally close trajectories and of the unpredictability of the system and gives a good characterization of the underlying dynamics.

Starting from the reconstructed attractor **X**, it is possible to compute, using the method of Sano and Sawada [20, 21], the SLE consisting of exactly $n = D_E$ exponents. This method is a qualitative one, and in the presence of a positive exponent, λ_1, a more accurate method is necessary for the computation.

The method of Rosenstein *et al.* [22] is used to compute the MLE from the time series. This method measures, in the reconstructed attractor, the average divergence of two close trajectories in the time $d_j(i)$. This can be expressed as:

$$d_j(i) = C_j e^{\lambda_1 (i\Delta t)}, \quad (3)$$

where C_j is the initial separation. By taking the logarithm of both sides we obtain:

$$\ln d_j(i) = \ln C_j + \lambda_1 (i\Delta t). \quad (4)$$

This is a set of approximately parallel lines (for $j = 1, 2, \ldots, M$), each with a slope roughly proportional to λ_1. The MLE is easily calculated using a least-squares fit to the average line defined by

$$y(i) = \frac{1}{\Delta t} \langle \ln d_j(i) \rangle, \quad (5)$$

where $\langle \cdot \rangle$ denotes the average overall values of j. Figure 6 shows a typical plot of $\langle \ln d_j(i) \rangle$: after a short transition there is a linear region that is used to extract the MLE.

4 RESULTS AND DISCUSSION

The signal is characterized by highly complex patterns in which different transients with both periodic and apparently aperiodic features can be identified. Figure 1 shows a part of the analyzed time series. The apparently random behavior of the numerical series, easily detectable by a simple visual inspection of the sound pattern, was confirmed by the amplitude spectrum reported in Fig. 2 and by the spectrogram in Fig. 3 whose inspection clearly shows the two main frequencies immersed in a large area of noise concentration. The false nearest neighbors method [23] provided an embedding dimension $m = 6$, while the method of the mutual information [19] suggests a value $T = 3$ for the delay time. A three-dimensional projection of a 1000-point long portion of the reconstructed attractor

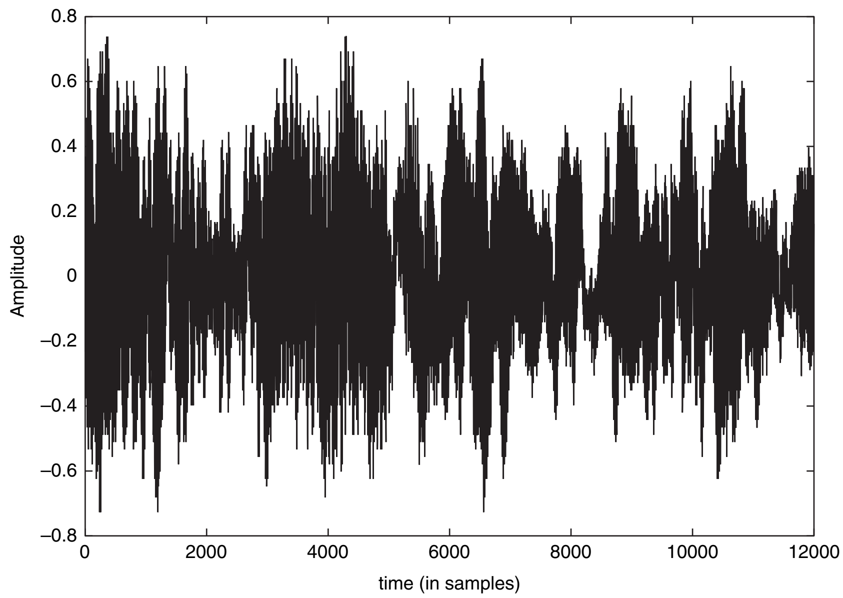

Figure 1: The analyzed signal showing the irregular behavior.

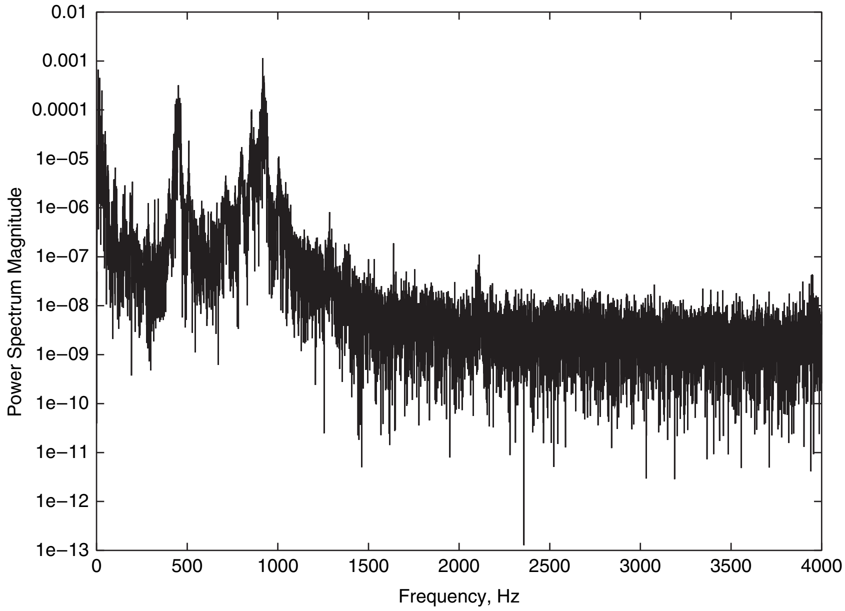

Figure 2: The power spectrum of the analyzed time series.

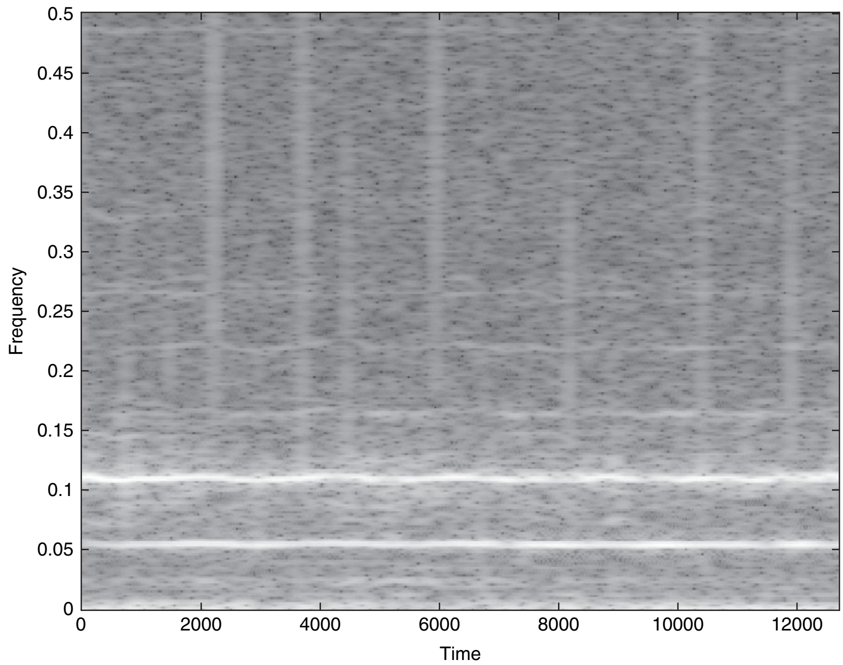

Figure 3: Spectrogram of the analyzed time series. The two main frequencies are immersed in a large noise concentration area, usually related to chaotic or irregular behaviors.

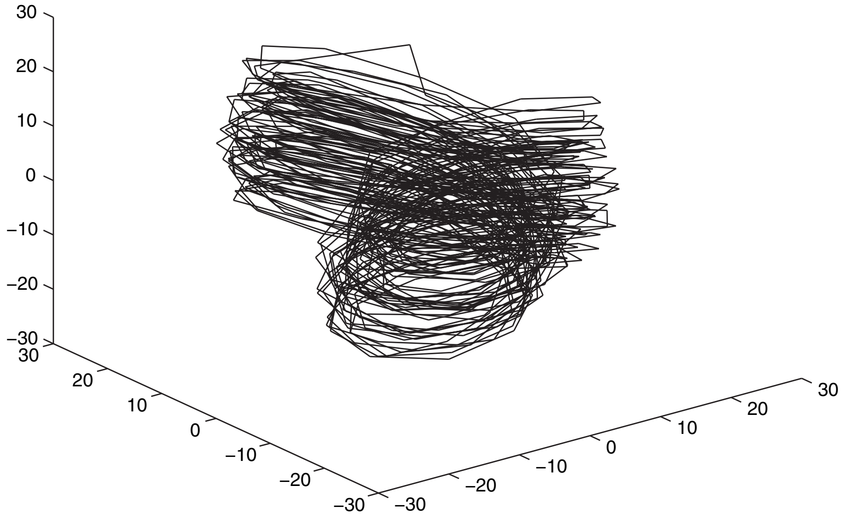

Figure 4: The three-dimensional projection of the attractor reconstructed using $T = 3$ and $D_E = 6$. The structure reveals the deterministic behavior of the signal.

is shown in Fig. 4. It is worth noting that, in spite of the apparent randomness of the vocal emission signal, the attractor structured qualities suggest an underlying deterministic dynamical evolution.

In order to carefully characterize the nature of vocalization dynamics, the SLE was evaluated. Average values of Lyapunov exponents are reported in Fig. 5 as a function of the number of steps forward L [17, 18, 24]. Each point is obtained by following and averaging the behavior of two nearby trajectories for L steps of the sampling time forward over 3000 initial locations on the attractor.

Owing to the lack of information on the dynamical operator mapping the reconstructed attractor, the evaluation of the six Lyapunov exponents from the experimental time series requires an approximate reconstruction of the unknown dynamics. The number of active dynamical degrees of freedom, D_E, corresponding to the number of Lyapunov exponents, was previously evaluated by the application of the local false nearest neighbors method [18]. The occurrence of two positive Lyapunov exponents points out the hyperchaotic nature of the vocalization behavior investigated. The Kaplan–Yorke fractal dimension D_L of the attractor [25], equal to $D_L = 4.11$, confirms the high dimensional fractal qualities of the strange attractor. 'Chaoticity' is also confirmed by the measure of the MLE. The value of $\langle \ln d_j(i) \rangle$ is reported in Fig. 6 as a function of the time $i\Delta T$.

Following the method suggested by Abarbanel, in order to avoid the pitfalls of the exponential law and then a false chaos detection, the algorithm was applied for different increasing values of the embedding dimension D_E. A false detection occurs when the obtained curves tend to bend down. Figure 6 clearly shows that the bending is missing. The exponent was computed by performing a linear regression in the range 30–50 iterations where slopes are constant for different D_E values. Therefore, a set of approximately parallel lines was obtained, each with a slope roughly proportional to the largest Lyapunov exponent. A value of $\lambda_1 = 0.0105$ was found (Table 1). The result was further corroborated by the analysis of a randomized temporal series, which does not present any linear region. The behavior is instead similar to that obtained from a random series. This result indirectly confirms the chaotic and deterministic nature of the signal analyzed.

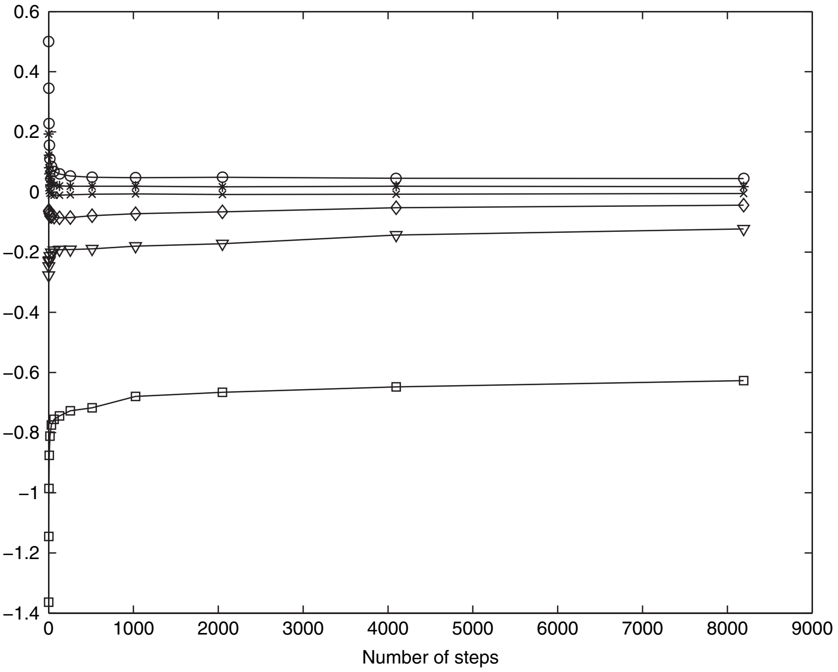

Figure 5: The average Lyapunov exponents as a function of the number of steps forward L in each location. The values are reported in units inverse of the sampling time (8050 Hz).

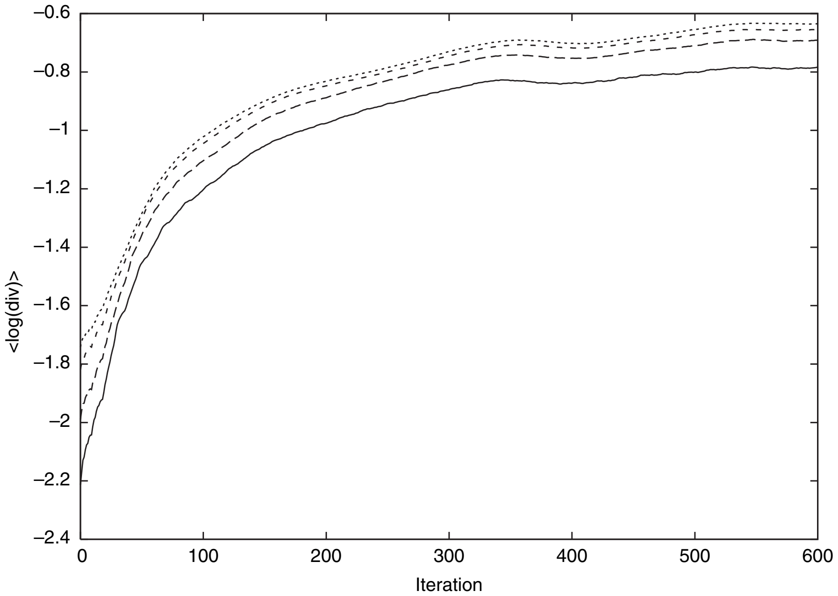

Figure 6: Results of the computation of the largest Lyapunov exponent. The value $\lambda_1 = 0.0105$ was found by performing a linear regression of the curves in the zone 30–50.

Table 1: Results of the analysis.

Parameter	Value
Delay time T	3
Embedding dimension D_{E}	6
Kaplan–Yorke dimension D_{L}	4.11
Maximum Lyapunov exponent λ_1	0.0105

5 CONCLUDING REMARKS

In spite of the experimental difficulties due to the presence of noise, echoes and superposition of vocalizations from different whales, nonlinear dynamics analysis has demonstrated the occurrence of chaos in the dynamics of sound emission from the humpback whale. Preliminary results seem to suggest that the vocalizations originate from air circulation inside the respiratory system of the whale. Unfortunately, any detailed hypothesis on the possible relationships between the observed nonlinear chaotic behavior of the vocal emission and the related physiological activities of the respiratory apparatus is restricted by the low degree of knowledge about the latter. Whether or not vocalization behavior could be classified according to the characteristics of its chaotic dynamics is still the subject of investigation. Further progress in this direction is expected from a systematic investigation of vocalizations emitted by whales under different circumstances.

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