Edinburgh, Scotland
EURONOISE 2009
October 26-28

Underwater ambient noise analysis using wavelet transform and empirical mode decomposition methods

Altynbek Isabekov[1]
Tayfun Akgul[2]
Suleyman Baykut[3]

Electronics and Communications Engineering Department
Istanbul Technical University
34469, Istanbul, Turkey

ABSTRACT

In this study, underwater ambient noise (UWAN) data are analyzed by means of wavelet based (WT) and empirical mode decomposition based (EMD) methods. The UWAN data sets are gathered by our custom-made "Bosporus Ambient Noise Acquisition System" (BANAS) in the Strait of Istanbul. The data set consists of two subsets of signals recorded during two different states: (i) in the absence of ship traffic and (ii) in the presence of ship traffic in the line of sight. For signal characterization, the WT and EMD methods, which are both known to be appropriate techniques for non-stationary data analysis, are applied. Analysis of the variances of both the wavelet detail coefficients (WDC) and intrinsic mode functions (IMFs) show that the variances of the first six consequent WDCs (corresponding to the frequency range of 40-2500 Hz) and the variances of the first five IMFs of the signals collected during the periods of various ships' cruising are found to be greater than the variances of the corresponding WDCs and IMFs collected in the tranquil sea. It is observed that the WDC and IMF variances reveal useful information about ship presence nearby the recording system yielding solutions to ship traffic density estimation problems.

1. INTRODUCTION

“Bosporus Ambient Noise Acquisition System” was designed and constructed in the scope of the “Measuring, Archiving and Modeling of Underwater Ambient Noise in the Strait of Istanbul” project which is executed by Istanbul Technical University (ITU) Signal Processing Laboratory and supported by The Scientific and Technological Research Council of Turkey (TUBITAK). The system consists of 8 hydrophone array, recording equipment and transmission lines[1]. All the data is gathered in the stait of Istanbul which is also known as “the Bosporus”. This strait is an approximately 30 km long, 1km wide channel that connects the Black sea with the Sea of Marmara. The dept varies between 30 m and 100 m. Here, the sea conditions are quite different than thoes in calm, deep

[1] Email address. altynbek.isabekov@gmail.com
[2] Email address. tayfun.akgul@itu.edu.tr
[3] Email address. baykut@itu.edu.tr

water. The Bosporus has a heavy ship traffic density with more than 50,000 passing ships per year. This number is increasing every year. Furthermore, the strait is preferential fishing place with quite a big number of fishing boats. Ferries which carry people between Asian and European sides of Turkey are also active during whole year. The data used in this study is collected at various sites in Bosporus shown in Figure 1.

Figure 1: UWAN measurement points in the Strait of Istanbul (Google Maps view).

During gathering of the signals, ship traffic and weather conditions were recorded to a logbook by an observer located nearby the station. Two classes are defined according to two different states: UWAN data collected (i) in the absence of ship traffic and (ii) in the presence of ship traffic in the line of sight. A signal segment gathered during absence of traffic is shown in Figure 2 a) and its power spectral density is plotted in Figure 2 b). An example to UWAN recorded in the presence of a ship is given in Figure 3 a) and its power spectral density is shown in Figure 3 b). The aim of this research is to identify the classes using recently developed techniques. Collected underwater ambient noise data is stored and then analyzed using wavelet transform based and empirical mode decomposition based methods. Studies reveal that underwater noise data show non-stationary behavior in the presence of ship traffic. Therefore instead of classical Fourier transform based spectral methods these two alternative techniques are applied. These methods are more reliable due to the fact that they do not require data to be stationary. In Section 2 brief descriptions of these two methods are given, in Section 3 analysis, discussion and the results are presented.

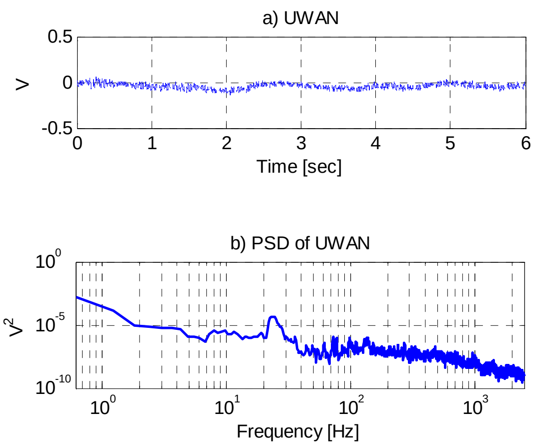

Figure 2: a) UWAN signal recorded in the absence of ship traffic; b) Its power spectral density.

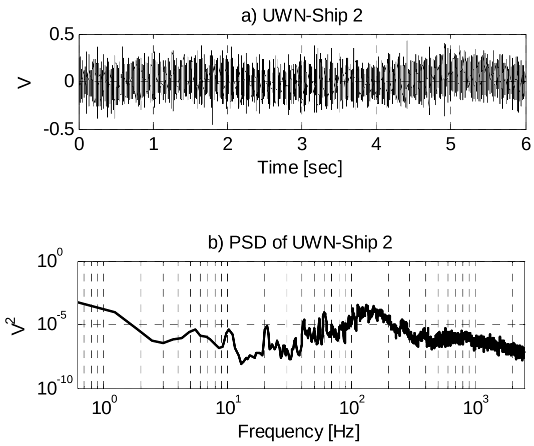

Figure 3: a) UWN signal recorded in the presence of a ship; b) Its power spectral density.

2. USED METHODS

In this section wavelet transform and empirical mode decomposition methods are briefly described. Definition and application of discrete dyadic wavelet transform are given. The dyadic filter bank property of the discrete dyadic wavelet transform is used in the analysis of the UWAN signals. Alternatively, empirical mode decomposition and intrinsic mode functions are described and the algorithm used in EMD is summarized. For clear comprehension, a visual example to sifting process is also provided.

A. Discrete Dyadic Wavelet Transform

Wavelet transform provides multi-resolution analysis of the signals. This method is based on measuring correlation between signal and the mother wavelet function, which is being shifted (translated) and scaled in the time span[2]. If the scale and the translation is discretized and varied as the powers of two, then discrete dyadic wavelet transform is obtained:

$$X_j(k) = 2^{j/2} \sum_{n=-\infty}^{\infty} x(n)\psi(2^j n - k), \qquad j,k \in \mathbb{Z} \tag{1}$$

where $x(n)$ is the analyzed signal, ψ is the mother wavelet, j is scale and k is translation indices. $X_j(k)$ is the detail wavelet coefficient at the j^{th} scale. It is known that dyadic wavelet transform acts like a dyadic filter bank and this crucial property is used in this research. In Figure 4 frequency ranges of the detail coefficients at different scales are given. In this study, variances of the wavelet coefficients are calculated using equation (2) where N is the length of $X_j(k)$.

$$\mathrm{var}\{X_j\} = \sum_{k=1}^{N} X_j^2(k)/N - \left(\sum_{k=1}^{N} X_j(k)/N\right)^2 \tag{2}$$

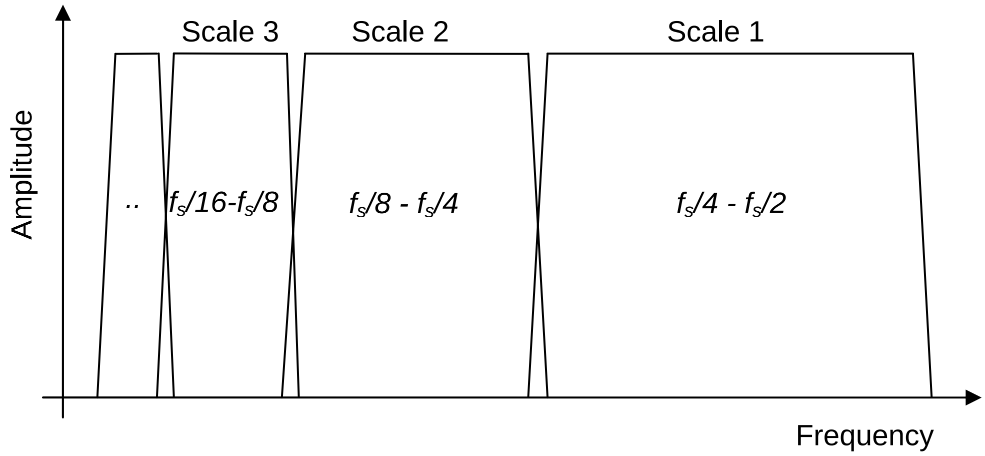

Figure 4: Discrete dyadic wavelet transform as a dyadic filter bank.

B. Empirical Mode Decomposition

Empirical mode decomposition is a powerful method for the analysis of non-stationary signals[3]. It should be noted that EMD does not yet have exact mathematical formulation and can only be described by an algorithm. In EMD, the signal is decomposed into intrinsic mode functions (IMFs) of finite number by passing through a so-called "sifting process". In contrast to classical methods, sifting process does not require a base function[3]. This makes EMD analysis totally adaptive to the nature of the signal. In EMD the analyzed signal is expressed as below:

signal = slow oscillations + fast oscillations superimposed on slow oscillations.

The main idea of this method is to decompose the signal into IMFs which are found by catching local oscillations within the signal. The signal $x(t)$ can be expressed as:

$$x(t) = r(t) + \sum_{j=1}^{J} c_j(t) \quad (3)$$

where $x(t)$ is the analyzed signal, J is the total number of IMFs, $c_j(t)$ is the j-th IMF and $r(t)$ is the residue left after sifting of the $x(t)$ signal. For a discrete-time signal of a length N number of the IMFs J can be estimated using the following equation:

$$J \approx log_2(N) \quad (4)$$

Note that IMFs have two important properties:

1. The number of local extrema points and the number of zero-crossings in the IMF are equal or differ at most by one.
2. At any time instant mean value of the upper envelope defined by local maxima and the lower envelope defined by local minima is equal to zero[3].

Second property implies that the envelopes of IMFs should be symmetric with respect to time axis. EMD procedure is explained below:

EMD Process

The intrinsic mode functions of the signal are estimated by operation defined by the following steps:

1. Local minima and local maxima points of the $x(t)$ signal are marked.
2. A line is fitted between local maxima points (generally by means of cubic spline interpolation). The same operation is applied to local minima points. These lines represent upper and lower envelopes $e_{max}(t)$ and $e_{min}(t)$
3. Average oscillation $m(t)$ (mean envelope) of the signal is obtained by taking an average of these envelopes:

$$m(t) = \frac{e_{max}(t) + e_{min}(t)}{2}$$

4. Average oscillation is extracted from the original signal:

$$d(t) = x(t) - m(t)$$

5. IMF test is applied to the signal $d(t)$. If $d(t)$ does not possess properties of an IMF, then the steps depicted above are repeated on $d(t)$. Otherwise, the sifting process is stopped and the first IMF of the original signal $x(t)$ is obtained. This IMF is subtracted from the original signal $x(t)$ and the first four steps are applied to the residual signal. This process is repeated until all the IMFs are found[3].

First four steps of the procedure represent sifting process where overall algorithm is called EMD process. In Figure 5, single step iteration of the sifting process is shown as an example. It is known that in the second step implementation of the “cubic spline” method for the interpolation gives good results[4]. The power of the residue signal is used as a criterion for termination of the sifting process. If the power of the residue is under some threshold then the iteration is stopped. For the threshold usually a relatively small percentage of the original signal is used as the threshold. EMD analysis can be considered as an adaptive filter bank similar to those in the wavelet transform[5]. In this study EMD is used to decompose the UWAN signals into intrinsic modes with different frequency contents. Then the variances (energies) of these modes are compared for two different classes of data: the signals recorded in the presence of ship traffic and the signals recorded in the absence of ship traffic in the line of sight. Variances of the IMFs can be calculated according to equation (5) where c_j is the j-th IMF and N is length of the signal.

$$\mathrm{var}\{c_j(k)\} = \sum_{k=1}^{N} c_j^2(k)/N - \left(\sum_{k=1}^{N} c_j(k)/N\right)^2 \qquad (5)$$

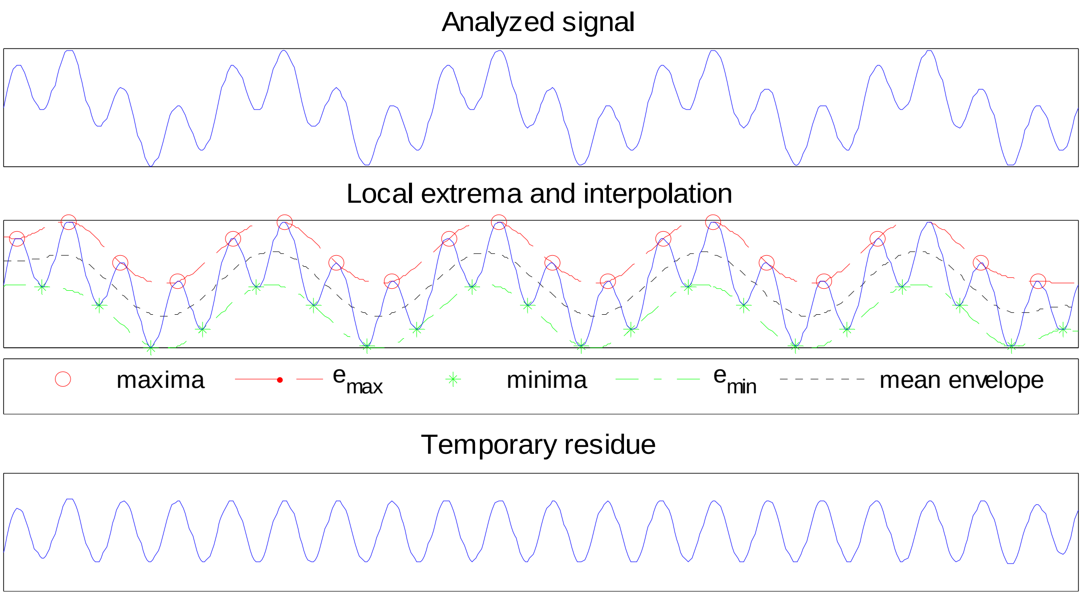

Figure 5: One iteration of the sifting process.

3. ANALYSIS AND RESULTS

Six data sets corresponding to cruising of six ships and four data sets of relatively tranquil environment with no ship traffic in the line of sight were analyzed. The sampling frequency of A/D converter was selected as 5000 Hz. Data analysis was performed in the MATLAB® environment. Length of all noise data sets was chosen as 6 seconds.

In Figure 6 variances of the wavelet coefficients obtained from dyadic wavelet decomposition of the underwater ambient noise data, which were taken while sailing of six different ships, are shown. Solid line represents average variances of the wavelet coefficients of the signal recorded in the absence of ship traffic. It is observed that variances of the first six wavelet detail coefficients of the underwater noise recorded in the presence of ship traffic are greater by 15-20 dB than the variances of the same coefficients pertaining to the signals recorded in the absence of ship traffic. It should be noted that first six wavelet coefficients correspond to the frequency range of 40-2500 Hz.

In Figure 7 variances of IMFs of the underwater ambient noise signals, which were recorded in six different time periods in the presence of six different ships, are shown. The number of IMFs for signals in both classes varies from 13 to 15 as required by equation (4). Solid line represents average variances of the IMFs of four data sets recorded during absence ship traffic in the line of sight. First IMFs, which represent fast oscillations, are located on the right side of the plot. In Figure 7 results similar to those in the wavelet transform analysis can be observed. Behavior of the first five IMFs' variances of the signals recorded in the presence of ship traffic are greater by 15-20 dB than the signals recorded in the absence of ship traffic in the line of sight. This observation may be used for estimation of ship traffic density.

ACKNOWLEDGMENTS

This work is supported by The Scientific and Technological Research Council of Turkey, Project No: 106Y090. The authors would like to thank Suheyl Belviranli for his help.

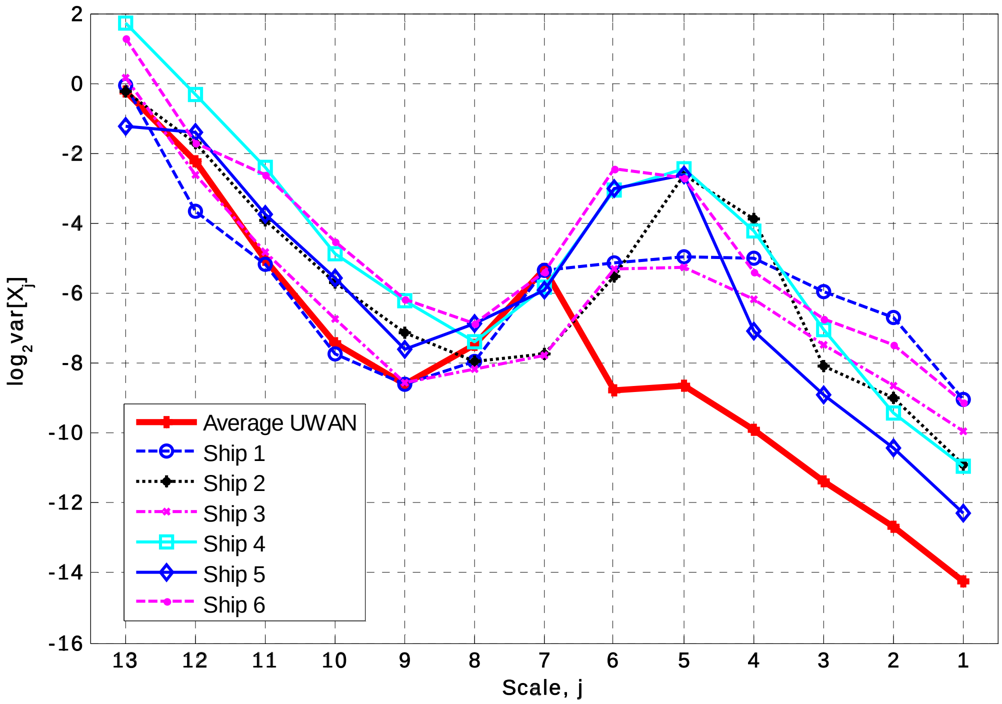

Figure 6: Variances of the wavelet coefficients pertaining to two classes of data: UWN recorded in the presence of ship traffic in the line of sight and UWAN recorded in the absence of ship traffic. Solid line represents average variances of the second class.

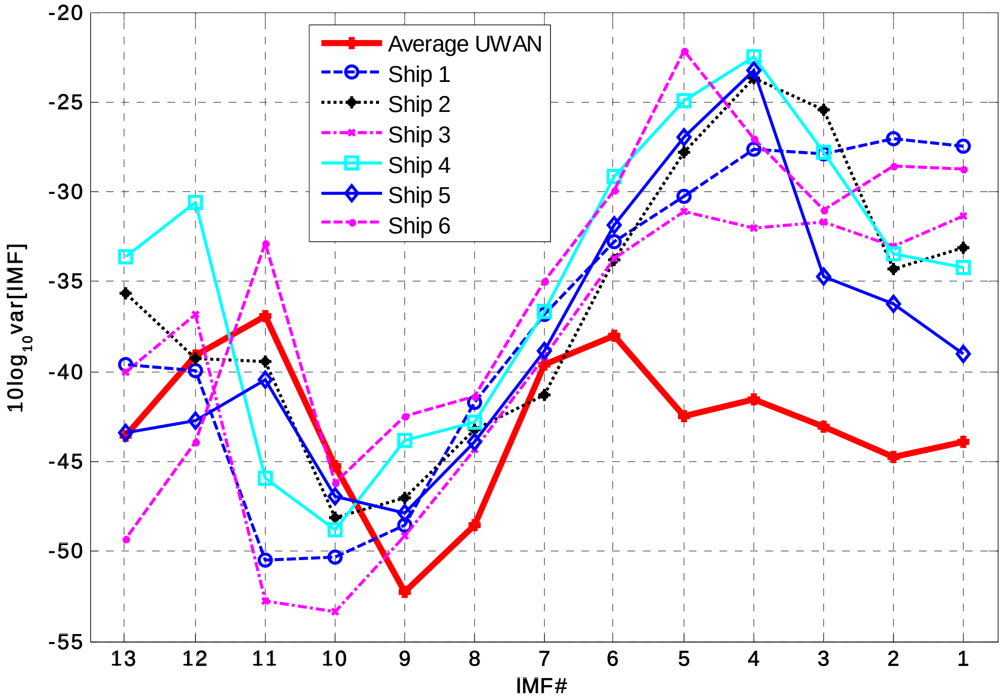

Figure 7: Variances of the IMFs pertaining to two classes of data: UWN recorded in the presence of ship traffic in the line of sight and UWAN recorded in the absence of ship traffic. Solid line represents average variances of the second class.

BIBLIOGRAPHY

[1] U. Ulug, T. Akgul and C. Gezer, “Ambient noise measurements in the Strait of Istanbul”, *Conference on Underwater Noise Measurement, Impact and Mitigation*, Southampton, 2008, pp. 35-42.

[2] C.S. Burrus, R. A. Gopinath and H. Guo, Introduction to wavelets and wavelet transforms, Prentice-Hall, New Jersey, 1998, pp. 8-9.

[3] N.E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N. C. Yen, C. C. Tung and H. H. Liu, The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis, *Proceedings of the Royal Society of London A.*, **454**, pp. 903-995, (1998).

[4] G. Rilling, P. Flandrin and P. Gonçalves, "On Empirical mode decomposition and its algorithms," *IEEE-EURASIP Workshop on Nonlinear Signal and Image Processing NSIP-03*, Grado, 2003.

[5] P. Flandrin and P. Gonçalves, Empirical mode decomposition as data-driven wavelet-like expansions, in *Internatonal Journal of Wavelets, Multiresolution and Information Processing*, **2,** No. 4**,** pp. 477-496, (2004).