Indian Journal of Science and Technology Vol. 3 No. 2 (Feb 2010) ISSN: 0974- 6846

Deconvolution methods for biomedical signals analysis

Mohammed A. Al-Manie
Computer Research Institute, KACST P.O. Box 6080, Riyadh 11442, Saudi Arabia.
manie@kacst.edu.sa

Abstract

In this paper, a deconvolution approach based on time frequency representation (TFR) methods is used for the estimation and analysis of biomedical signals. Chosen as examples are electroencephalogram (EEG) as well as the Electrocardiogram (ECG) signals for normal and abnormal patients. In particular, an iterative procedure is applied to calculate the required time-frequency distributions for the different types of cases under study. The deconvolution method can be defined as the process of recovering the input to some system from its output given information about that particular system. This kind of procedure is used in the field of time-frequency analysis for enhancing the resolutions of the signals under testing. These advantages are used in this paper for the biomedical applications area.

Keywords: Sleep scoring, electroencephalogram, electrocardiogram, deconvolution.

Introduction

Biomedical applications using signal processing techniques is a major area of interest that has been investigated by a large number of scientific researchers (Penzel & Conradt 2000; Hassanpour *et al*., 2004). For instance, in psychiatric medicine sleep scoring based on electroencephalogram (EEG) is a very important tool used for diagnosing patinas. The sleep scoring process accomplished by EEG signal analysis is usually used to detect any abnormalities or study the behavior of brain waves for a particular mental disease such as epilepsy. In order to perform sleep staging, the characteristics waves produced during sleep such as delta, alpha, theta, beta, spindles, and K-complexes must be detected and classified. Analysis of EEG data is a challenging problem due to the fact that the signal is multi-component and very non-stationary.

Consequently, both period analysis which is a time domain method performed as a zero-crossing or a peak detection of the wave form and frequency-domain analysis approach through the fast Fourier transform (FT) are not enough to represent the non-stationary behavior of these waves especially with the presence of transients. The main problem of spectral analysis using the FT is the assumption that the signal portion being analyzed is stationary within a certain chosen window length. Also, in this case the frequency resolution is limited to half the sampling rate being the highest possible frequency that can be estimated. Therefore the need arises to study this problem in a more accurate and comprehensive approach. An alternative method is the time-frequency analysis procedures, which makes it possible to represent the biomedical signal under study in time and frequency simultaneously. Several researchers have attempted this approach for this type of application.

Hassanpour *et al*. (2004) presented some work on EEG spike detection using a time-frequency (TF) analysis. In particular, the Choi-Williams (CWD) distribution is adopted in order to reduce the cross-terms interference. This type of approach is considered reliable in the presence of the non-stationary spikes in a non-stationary background. In this experiment, singular value decomposition was also used for noise reduction. The sampling frequency for the test data collected for a newly born baby is 256 Hz which was used to test the time-frequency method's performance.

On the other hand, Shimada *et al*. (2000) in an experiment, implemented neural networks for the purpose of characteristic waves detection of sleep EEG. The EEG data was arranged into a two dimensional matrix where each element is introduced to the corresponding cell of the input layer. The used sampling rate for data collection is 200 Hz with a Hamming window of 128 points in length. The input data window or the input layer is shifted by 64 points during EEG data processing. The types of characteristic waves used in the training process included spindles, humps, alpha and background noise.

Furthermore, the study of the time-varying potential produced by the heart known as Electrocardiogram (ECG) signals is one of the major areas of research in biomedical signal processing (Kotsaa *et al*., 1993; Paul *et al*., 1999). The ECG signal, which comprises major activities of the heart, is mainly made up of three major components; the P wave represents arterial activation, the QRS complex represents ventricular depolarization and the T wave represents ventricular re-polarization. Since these types of waves have specific shapes in the time-domain as well as in the frequency-domain, then the physician can detect any abnormalities in the cardiac system through observation of the ECG signal.

For instance, Paul *et al*. (1999) presented a method known as the cepstrally transformed discrete cosine transform (CTDCT) to analyze electrocardiography data with wide QRS deflection. Another proposed procedure by Sivannaryana *et al*. (1999) is to estimate the ECG parameters using the multi-scale analysis of the biorthogonal wavelet transforms. A bank of symmetric low pass filters (LP) and anti-symmetric high pass (HP) are implemented as the basis function to find the required parameters. In a review paper, Maglaveras *et al*. (1998) discussed a number of ECG recognition and classification methods including non-linear transformation, neural networks (NN), and non-linear principle component analysis (NLCPA). The paper, described some estimation techniques such as the preprocessing stage, identification of waves of interest, segments boundaries, transformation procedures, data training, and algorithm performance measures.

Fig. 1 Time series representation of the ECG signal-wave form

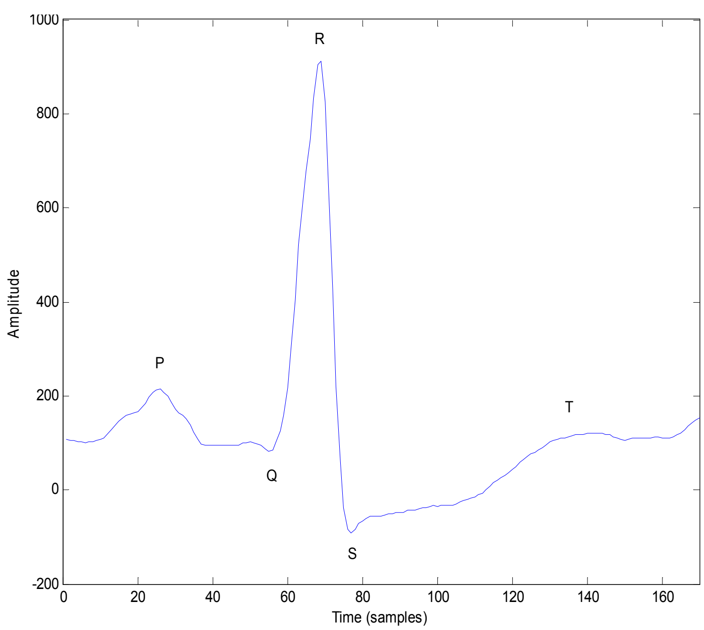
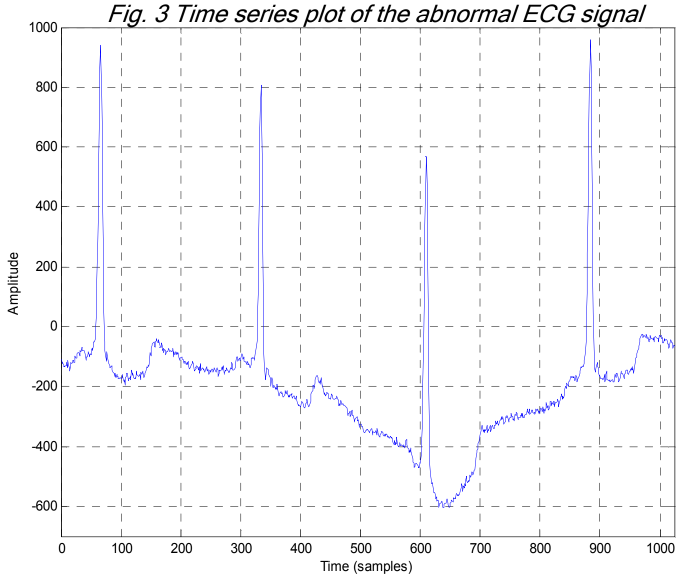


Fig. 3 Time series plot of the abnormal ECG signal



In the Second section of this paper, the theory needed to perform the proposed method is discussed. The third section presents a discussion of findings and suitability of the algorithm for the biomedical signal analysis. In the other hand, the final part provides a summary of work such as advantages, disadvantages related to this particular application including final conclusions.

Theoretical backgrounds

In this section, a discussion of the required theory and mathematical background needed for the implementation of the time-frequency deconvolution is presented. This procedure has the ability to recover the

Fig. 2 Time series plot of the normal ECG signal

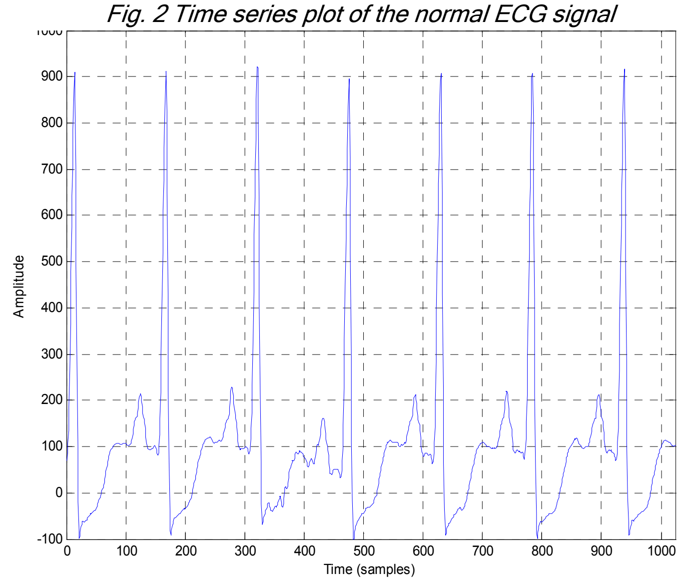
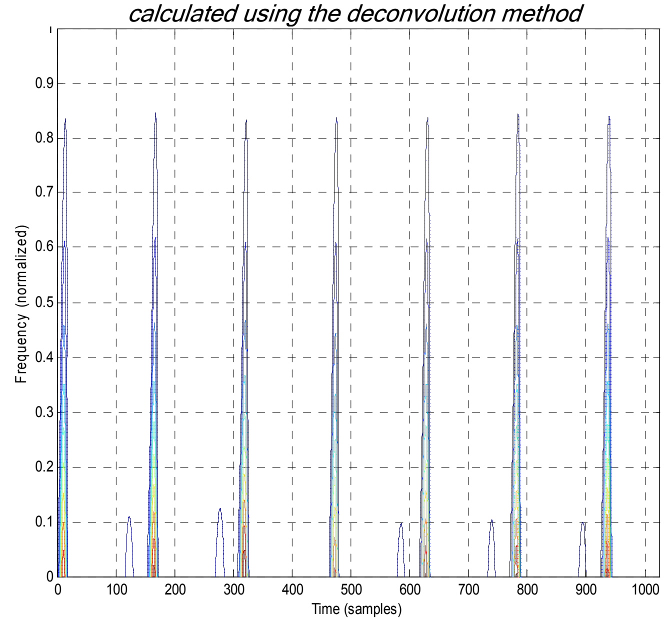


Fig. 4 Time-Frequency distribution of the normal ECG signal calculated using the deconvolution method



Indian Journal of Science and Technology Vol. 3 No. 2 (Feb 2010) ISSN: 0974- 6846

input given to a system. A number of researchers have attempted this problem where in many instances some constrains or assumptions had to be made such as considering the tested signal a stationary process within a selected window.

For ex, Shah *et al*. (1999) proposed a deconvolution method to recover the generalized transfer function of a time-varying filter which can be later used to estimate the time-frequency distribution. In a similar approach, the spectrogram is represented as a blurred version of the Wigner distribution. This approach is mathematically based on the fact that the Spectrogram can be written as the convolution of the Wigner-Ville estimate of some signal with the Wigner-Ville estimate of the window used to calculate the Spectrogram. The result obtained using this method is used to find the time-frequency distributions; in this case for biomedical signals. The resulting time-frequency estimate will be free from artifacts caused by the cross terms phenomena associated with the Wigner-Ville distribution.

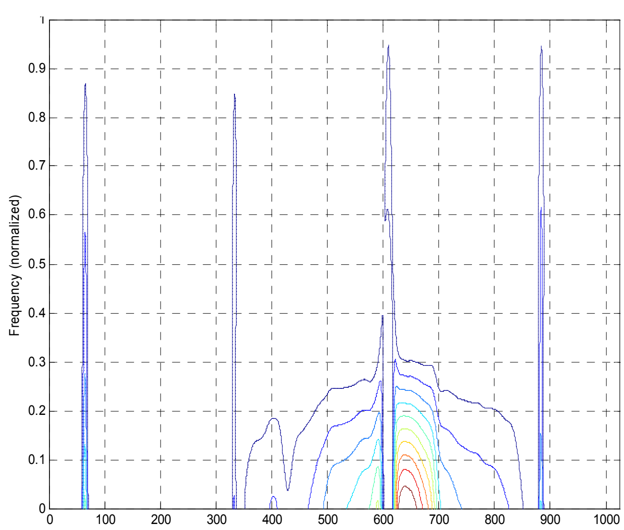
Consequently, to recover the un-blurred Wigner estimate, an iterative least square deconvolution algorithm should be used. The final answer is evaluated in terms of resolutions in the time-frequency plane as well as the ability to represent abnormalities and transients in the time-varying spectrum. The mathematical notation for the convolution equation used in this paper is in the following form (Emresoy, 1998):

$$S_{sp}(n,\omega) = S_W(n,\omega) ** B(n,\omega) \text{ ------------ (1)}$$

Where $S_{sp}(n,\omega)$ is the Spectrogram estimate represented as:

$$S_{sp}(t,\omega) = \left| \frac{1}{\sqrt{2\Pi}} \int s(\tau) h(\tau - t) e^{-j\omega\tau} d\tau \right|^2 \text{ --------- (2)}$$

Fig. 5. Time-frequency distribution of the abnormal ECG signal calculated using the deconvolution method



and $s(t)$ is the input signal, where $h(\tau - t)$ stands for a chosen window function. In equation 1, $S_W(n,\omega)$ is the Wigner-Ville distribution of the signal and $B(n,\omega)$ is the blurring function which is the Wigner-Ville distribution of the window function used to calculate the Spectrogram. The two star symbols stand for convolving twice i.e. in time as well as in frequency.

The desired estimate is obtained by recovering the un-blurred time-frequency distribution from equation 1. This objective is accomplished using an iterative least square deconvolution algorithm of the following form:

$$S_{i+1}(n,\omega) = S_i(n,\omega) + \lambda[S_{SP}(n,\omega) - B(n,\omega) ** S_i(n,\omega)] \text{ ------------- (3)}$$

Where the letter i represents the iteration number and λ is called a relaxation parameter used to enhance the convergence speed of the algorithm (Emresoy, 1998).

Results and discussion

In this Section, the proposed time-frequency de-convolution algorithm is applied to the collected biomedical signals. The final results obtained using this procedure are analyzed in terms of abilities to detect transients especially in the abnormal cases and evaluate the resulting time-frequency resolutions. The analysis method is applied to a typical ECG signal which has its main components illustrated in Fig. 1. The time-series representation of the ECG signal of length 1024 sampling points for a normal subject is shown in Fig. 2. The plot of Fig.3 depicts an ECG of the same length for an abnormal subject. Some variations in amplitude and shape of the signal are clearly present in this case. The suggested method is implemented for the aforementioned test waves.

Firstly, the iterative deconvolution algorithm was applied to the ECG signal collected for the normal subject with the time-frequency representation given in Fig. 4. As can be seen from this result, the proposed method was able to detect clearly the QRS complex, and the preceding P wave which represents various activities of the heart. Fig. 5 depicts the resulting time-frequency distribution for the ECG signal of the abnormal case. By comparison of this result with that obtained for the normal one (Fig. 4), the transients in this case are well represented in the time-frequency plane, indicating the ability of detecting abnormalities for this particular application.

Secondly, the same method is tested on another type of biomedical signals, namely the electroencephalogram (EEG) signal used in psychiatric medicine for sleep scoring to diagnose patinas. In Figure 6, a typical time-series plot of a normal EEG wave is shown with 512 samples in length. The time-frequency deconvolution approach is implemented to represent this multi-component and highly no-stationary signal. The result

Indian Journal of Science and Technology Vol. 3 No. 2 (Feb 2010) ISSN: 0974- 6846

Fig. 6 Time-series plot for the first epoch of an EEG signal

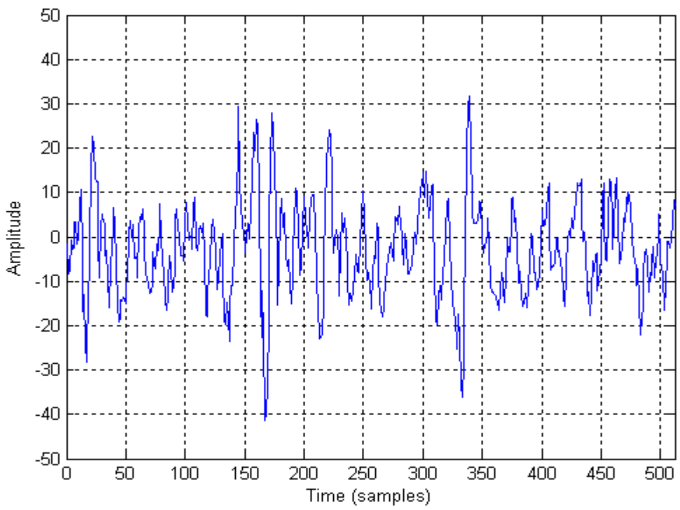


Fig.7. Time-frequency distribution for the first epoch of an EEG signal

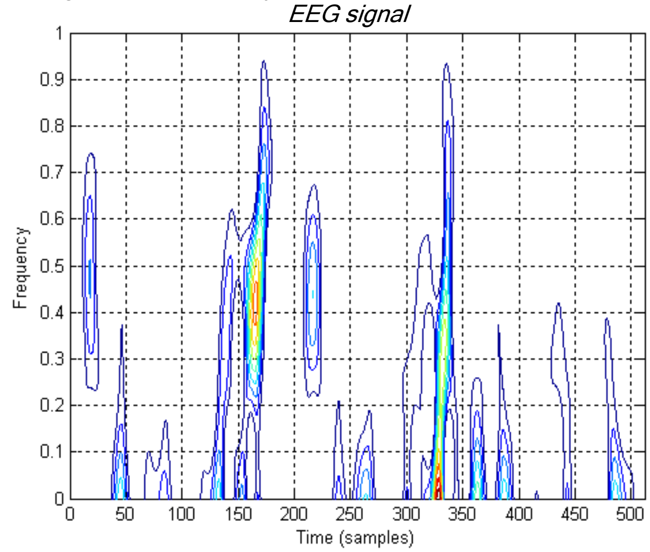


Fig. 8. Time-series plot for a second epoch of an EEG signal

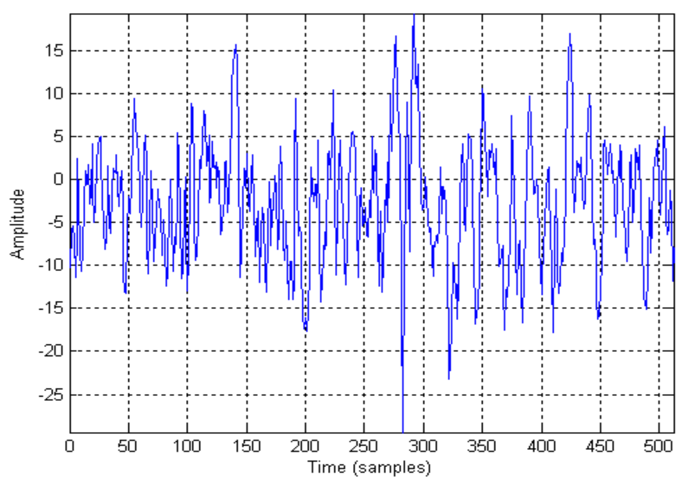


Fig. 9. Time-frequency distribution for the second epoch of an EEG signal

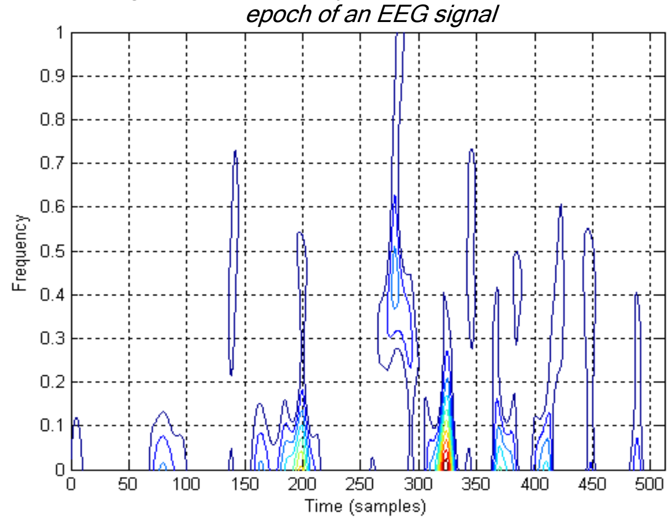


Fig. 10 Time-series plot for the third epoch of an EEG signal

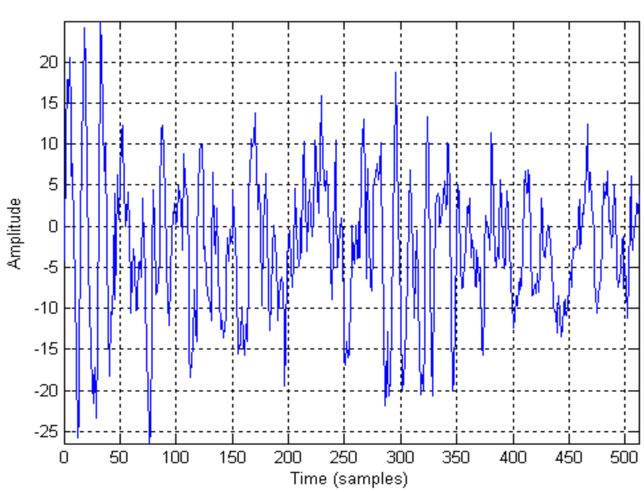
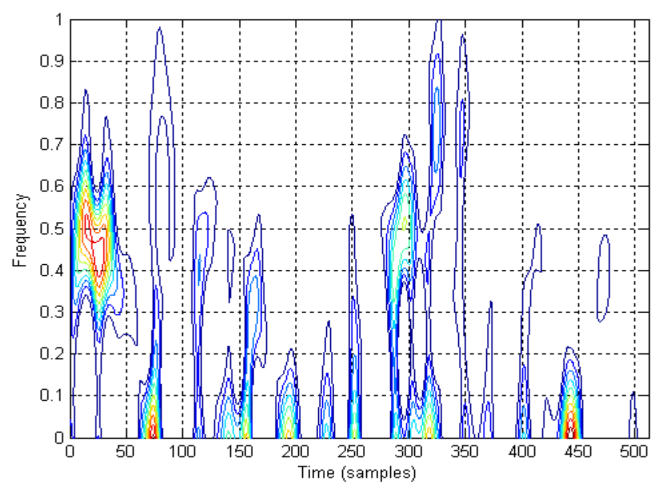


Fig. 11 Time-frequency distribution for the third epoch of an EEG signal.



depicted in Fig. 7 shows high energy at certain frequencies with the corresponding time of occurrences. A second epoch of the same length is also represented in Fig.8. The result of the proposed procedure is depicted in Fig. 9 with less activities and lower energies. On the other hand, Fig. 10 and 11 depict signal epochs of much higher energy than the previous ones. This is clearly revealed in the time frequency distribution of the various activities present in the tested EEG epoch.

Summary and conclusions

Time-frequency analysis based on a selected deconvolution technique was applied to biomedical signals for normal and abnormal subjects. The results obtained using this procedure provided a high resolution in time as well as in frequency. The disadvantage of the iterative deconvolution method is the time required to calculate the desired time frequency representation particularly with long duration test signals. The main advantage of this method is the ability to reveal the non-stationary behavior of this type of waves and detect any transits especially in the case of abnormal subjects, due to the two dimensional representation. Consequently, this method can be helpful in this particular field such as diagnosis of possible heart problems or in sleep scoring used to detect brain abnormalities.

Acknowledgment

The author would like to thank KACST for its financial support.

References

1. Emresoy M (1998) Evolutionary spectrum estimation by positively constrained deconvolution. *IEEE Trans. Signal Process*. 669-671.
2. Hassanpour H, Mesbah M and Boashash B (2004) EEG spike detection using time-frequency analysis. *ICASSP.* 5, 421-424.
3. Kotsaa P, Pappas C, Strintzis M and Maglaveras N (1993) Nonstationary ECG analysis using Wigner-Ville transform and wavelets. *Comp. Cardiol.* 499-502.
4. Maglaveras N, Stamkopoulos T, Diamantaras K, Pappas C and Strintzis M (1998) ECG pattern recognition and classification using non-linear transformations and neural networks: a review. *Int. J. Medical Informatics*. 52, 191-208.
5. Paul J, Reddy M and Kumar J (1999) A Cepstral transformation technique for dissociation of QRS-type ECG signals using DCT. *Signal Process*. 29-39.
6. Penzel T and Conradt R (2000) Computer based sleep recording and analysis. *Sleep Medicine Rev.* 47(2), 131-148.
7. Shah S, Chaparro L and El-Jaroudi A (1999) Generalized function estimation using evolutionary spectral de-blurring. *IEEE Trans. Signal Process.* 47 (8), 2335-2339.
8. Shimada T and Shiina T (2000) Detection of characteristic waves of sleep EEG by neural network analysis. *IEEE Trans. Biomedical Eng*. 47(3), 369-379.
9. Sivannarayana N and Reddy D (1999) Biorthogonal wavelet transform for ECG parameters estimation. *Medical Eng. Physics*. 21, 167-174.