International Journal of Medical, Medicine and Health Sciences
ISSN: 2517-9969
Vol:4, No:1, 2010

# Presenting a Combinatorial Feature to Estimate Depth of Anesthesia

Toktam Zoughi and Reza Boostani

*Abstract*—Determining depth of anesthesia is a challenging problem in the context of biomedical signal processing. Various methods have been suggested to determine a quantitative index as depth of anesthesia, but most of these methods suffer from high sensitivity during the surgery. A novel method based on energy scattering of samples in the wavelet domain is suggested to represent the basic content of electroencephalogram (EEG) signal. In this method, first EEG signal is decomposed into different sub-bands, then samples are squared and energy of samples sequence is constructed through each scale and time, which is normalized and finally entropy of the resulted sequences is suggested as a reliable index. Empirical Results showed that applying the proposed method to the EEG signals can classify the awake, moderate and deep anesthesia states similar to BIS.

*Keywords*—Depth of anesthesia, EEG, BIS, Wavelet transforms.

## I. Introduction

INJECTION of a certain volume of anesthetic drug into patients during surgery has been a challenging issue among anesthetic specialists [1]. By monitoring depth of anesthesia, specialists are able to control this depth during a surgery [2]. However, the main problem in this controlling is that injecting a high volume of an anesthetic drug like isoflurane drives the patient into a deep anesthesia which eventually leads to comma. Conversely, applying a low volume of such a drug maintains the patient's state near to the consciousness which may end up with the patient being awakened during the surgery [3, 4]. Specialists can monitor anesthesia depth using clinical symptoms such as blood pressure, heart beat, body movements, and breathing. In addition to the use of anesthetic agents, there are some other drugs like muscle relaxing drugs, breathing regulators, pain killers, and tranquilizers which make the interpretation of anesthetic symptoms difficult. Since these drugs mostly affect the brain, the researchers' attention is entirely drawn to the analysis of electroencephalogram (EEG) signal [5]. In this way, there are two EEG-based practical approaches to determining the depth of anesthesia: auditory evoked potential (AEP) in which the excitability of a patient is measured according to his response to the audio stimulus [6, 7] and Bispectral index (BIS) [8] which represents the coupling of EEG frequencies and gives a value in the range of 0-100, which points to deep anesthetic state up to consciousness [9]. EEG signals behave irregularly; hence, it seems that fractal dimension can be an informative index for these signals but the main weaknesses of this method is that EEG signals contain non-uniform and complex fluctuations which generates different fractal dimension values for a certain brain state. Therefore, the main drawback of fractal dimension methods for analyzing these signals is the lack of robustness [10]. Through the last three decades, a lot of research has been performed to develop an efficient time-frequency representation of a signal [11]. In this way, several time-frequency techniques are designed for vast variety of applications according to signals characteristics [11, 12]. Generally speaking, time-frequency transforms can be divided into two main categories; linear and non-linear transforms. Linear transforms such as short time Fourier transform (STFT), wavelet transform (WT), packet wavelet and multi-wavelet transforms can reveal the frequency content of a signal in different scales in term of intensity while non-linear time frequency transforms such as Wigner-Ville and Choi-Williams transforms can reflect the energy distribution of a signal in the time-frequency domain [13].

CSE and IT Dept., Faculty of Electrical and Computer Engineering, Shiraz University, Shiraz, Iran (Corresponding author: Toktam Zoughi, e-mail: Tzoughi@cse.shirazu.ac.ir, phone: +987116271747, +989359401276).

CSE and IT Dept., Faculty of Electrical and Computer Engineering, Shiraz University, Shiraz, Iran (e-mail: boostani@shirazu.ac.ir).

## II. Materials And Methods

### A. Data Acquisition

In this study eleven subjects participated all of whom used the isoflurane anesthetic drug. However, their surgery and duration of their anesthesia were different. During anesthesia they were injected some additional drugs such as Pentanal (tranquilizer), Atracurium (muscle relaxer), Midazolam (pain killer) and isoflurane, which is the main drug that drives the patients into anesthesia [14-16]. Before injecting any drug, the patients were asked to lie down and relax for a few minutes. Then, injection of anesthetic drugs started till the time that patients were in the suitable anesthetic depth for surgery. Meanwhile, BIS index was determined in ten-second successive intervals simultaneous to recording the EEG signal. To record EEG signal, BIS-XP (Aspect Medical Systems of Norwood) instrument whose sampling frequency is 128Hz was used. A trial sample of EEG signal during the anesthesia is shown in Fig. 1 As it can be seen from Fig. 1, EEG signal in the higher anesthesia depth contain lower frequency component compared to the consciousness. In other words, as a patient is drawn to deep anesthesia, his/her efficient EEG frequency component decreases.

### B. The proposed algorithm

EEG content

According to several observations of EEGs in different states such as anesthesia, sleep, and hypnosis, researchers found out that the main informative frequencies are in the range of 0.3 and 30 Hz. This range is classified in a number of frequency bands as follows.

Delta (<4 Hz): delta rhythms are slow brain activities occur only in deep sleep stages of normal adults and pathologies.

Theta (4-8 Hz): these frequencies occur in normal infants, children and in adults during drowsiness and sleep states. Rarely theta rhythms appear in the normal waking adult. In abnormal and pathological conditions, high theta activity appears.

Alpha (8-14 Hz): alpha rhythms observe in normal adults during relaxation and mentally inactive awaked. The amplitude is mostly less than 50 mV and appears in the occipital area. Alpha rhythms are blocked by visual attention and other mental efforts such as thinking.

Beta (14-30 Hz): beta activity is mostly occurs in front-central region and its amplitude is less than alpha rhythms. It is observed in expectancy states and tension.

Gamma (>30 Hz): gamma rhythms have a high frequency band and usually are not considered by clinical and physiological interests therefore usually it is omitted in EEG analysis.

WT is an effective tool in signal processing due to its unique properties such as time-frequency localization (obtaining a signal at particular time and frequency interval, or extracting features at various locations in time at different scales) and multi-rate filtering (differentiating the signals having various frequencies). Using these properties one can extract the desired features from an input signal characterized by certain properties in time and frequency domains. Wavelet decomposes EEG signal into desired band, which would be effective for further analysis. For instance, when an EEG signal is decomposed in three scales, it looks likes to filter the signal into three frequency bands including 0-8, 8-16 and 16-32Hz, which are similar to theta together with delta, alpha and beta bands.

In this study, a new measure is introduced which is called Wavelet Coefficient Energy Entropy (WCEE) to provide quantitative information about the depth of anesthesia. Similar approaches were suggested in several studies such as the neurological status of the brain [27], ordering or disordering of EEG during sleep [28] and seizures [29, 30].

In order to calculate the WCEE, the wavelet coefficients $C_j(k)$ of that signal are calculated at each scale j. The SWT which is computed in de-noising step is also used to decompose the recorded EEG into different frequency scales. The energy at each scale j and time k can be calculated by the following equation:

$$E_j^{(k)} = |C_j(k)|^2 \quad (1)$$

where $E_j^{(k)}$, is the sum of the squared wavelet coefficients (energy). The total energy in the three scales is obtained by the following formula:

$$E_{tot} = \sum_j \sum_k |C_j(k)|^2 \quad (2)$$

The relative wavelet coefficient energy, which defines energy's probability distribution in time-scale, is defined as:

$$p_j^{(k)} = E_j^{(k)}/E_{tot} = |C_j(k)|^2/(\sum_j \sum_k |C_j(k)|^2) \quad (3)$$

Obviously, $\sum_k \sum_j p_j^{(k)} = 1$ since it is summation of probabilities. The proposed feature is entropy of the resulted samples in all scales and times which is called as WCEE and determined as follows:

$$H_{WT} = -\sum_j \sum_k p_j^{(k)}.log_2[p_j^{(k)}] \quad (4)$$

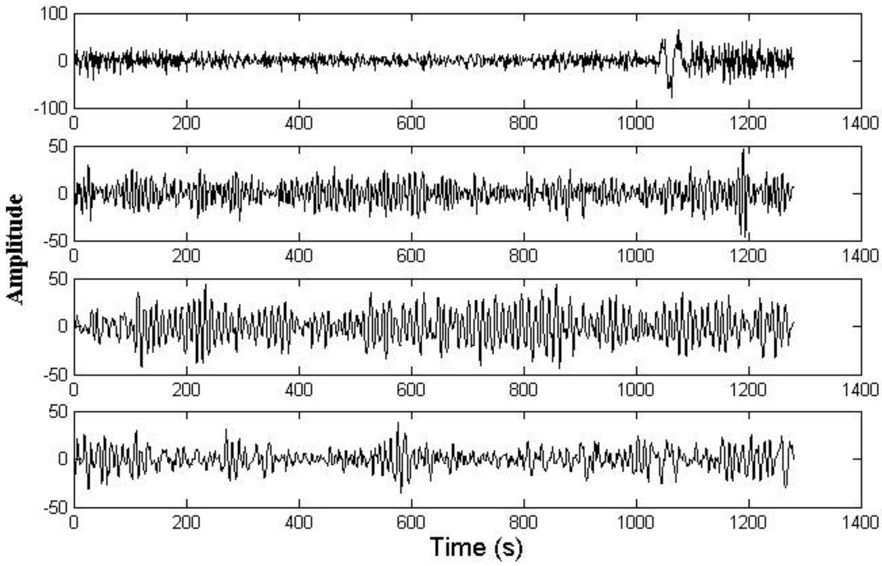


Fig. 1. Four ensembles of EEG signal of a patient during the surgery are shown above in which, from top to down, gradual changes of EEG signal when depth of anesthesia is increased is depicted. It can be observed that no significant relation between the amplitude

Here we obtain an index for each epoch namely $H_{WT}$ according to the equation (5). The value of this index is normalized between 0 and 100 (similar to BIS) and shows depth of anesthesia or patient states during anesthesia. The value of WCEE can provide a good estimation of anesthesia depth.

### *C. Post-processing*

After applying our algorithm, some postprocessing is performed to enhance the reliability of results. In this research, EEG signal is analyzed in each second but it leads to a very noisy index. For solving this problem we use averaging method in which for every 10-second epoch the average is computed and reported as the final index. This approach makes the obtained WCEE index comparable to the BIS [31]. As mentioned before, our algorithm computes SWT for preprocessing and determining the WCEE index. The main reason of choosing SWT is its low computational complexity that enables this transform to be employed in real-time applications like monitoring depth of anesthesia. In the next section, empirical evaluations to assess the proposed method are illustrated.

## III. Results And Discussion

To record EEG signal, BIS-XP instrument whose sampling frequency is 128Hz was used. EEG signals from eleven patients all of whom were used isoflurane during the surgery were recorded. The recorded time for all of the patients was not equal and it is totally equal to 1870 epochs. After applying the preprocessing stage in order to eliminate the ocular and ECG artifacts from EEG signals, the proposed WCEE index is extracted from the signals and the obtained results were compared to the BIS. The methods are implemented using MATLAB 2006. Analyzing one-second EEG leads to a very noisy index, thus, 10-second averaging filter is used for making it more robust and comparable to the BIS values. Fig. 2 depicts BIS index with respect to obtained WCEE index. In this figure, vertical axis shows BIS index and horizontal axis shows WCEE index. As illustrated in this figure, using the proposed method anesthesia states are well apart from each other in terms of moderate and high anesthetic depths and consciousness. As it is expected, in deep anesthesia, irregularity of EEG is decreased which leads to decrease scattering of wavelet coefficients; consequently, WCEE index which is entropy of the samples' energy is decreased. In contrast, in the moderate anesthesia state, irregularity increased that increasing the WCEE index in this state confirms the underlying changes in EEGs. BIS index of the four persons is depicted versus time in Fig. 3(a)s and the results of the WCEE index versus time illustrated in Fig. 3(b)s. As can be seen, the results achieved by the proposed method get very near to the BIS index in the deep and moderate anesthesia depths. In addition, most of the EEG based indexes are not scalable from one to another one. In other words, EEG indexes can follow the trend of variations but their values cannot be ranged from two certain values (0-100). This is a very positive property which makes our method scalable for different subjects and anesthesiologists can relay to our index. Nevertheless the proposed method suffers from lack of robustness compare to the BIS index.

## IV. Conclusion

In this study, an efficient method based on wavelet transformation for estimating the anesthesia depths is resented. The proposed method extracts informative features from the EEG signals during anesthesia. The ability of wavelet in decomposition EEG signal into various frequency bands makes it efficient tool to describe these signal. Since each level of anesthesia contains specific frequency bands, relation between these frequency bands would be a good interpretation of anesthesia depths. Thus, we use entropy of these coefficients to obtaining anesthesia indices. Hence, the main contribution of this paper is utilizing entropy of wavelet coefficients in a new way to determine the anesthesia depth and to provide more robust results. This method provides a good approximation of the anesthesia depths and its results is highly consistent

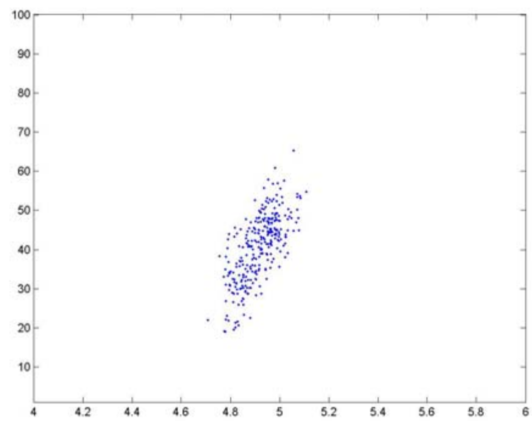


Fig. 2. Correlation of the index achieved by WCEE (horizontal axis) is compared versus BIS index (vertical axis).

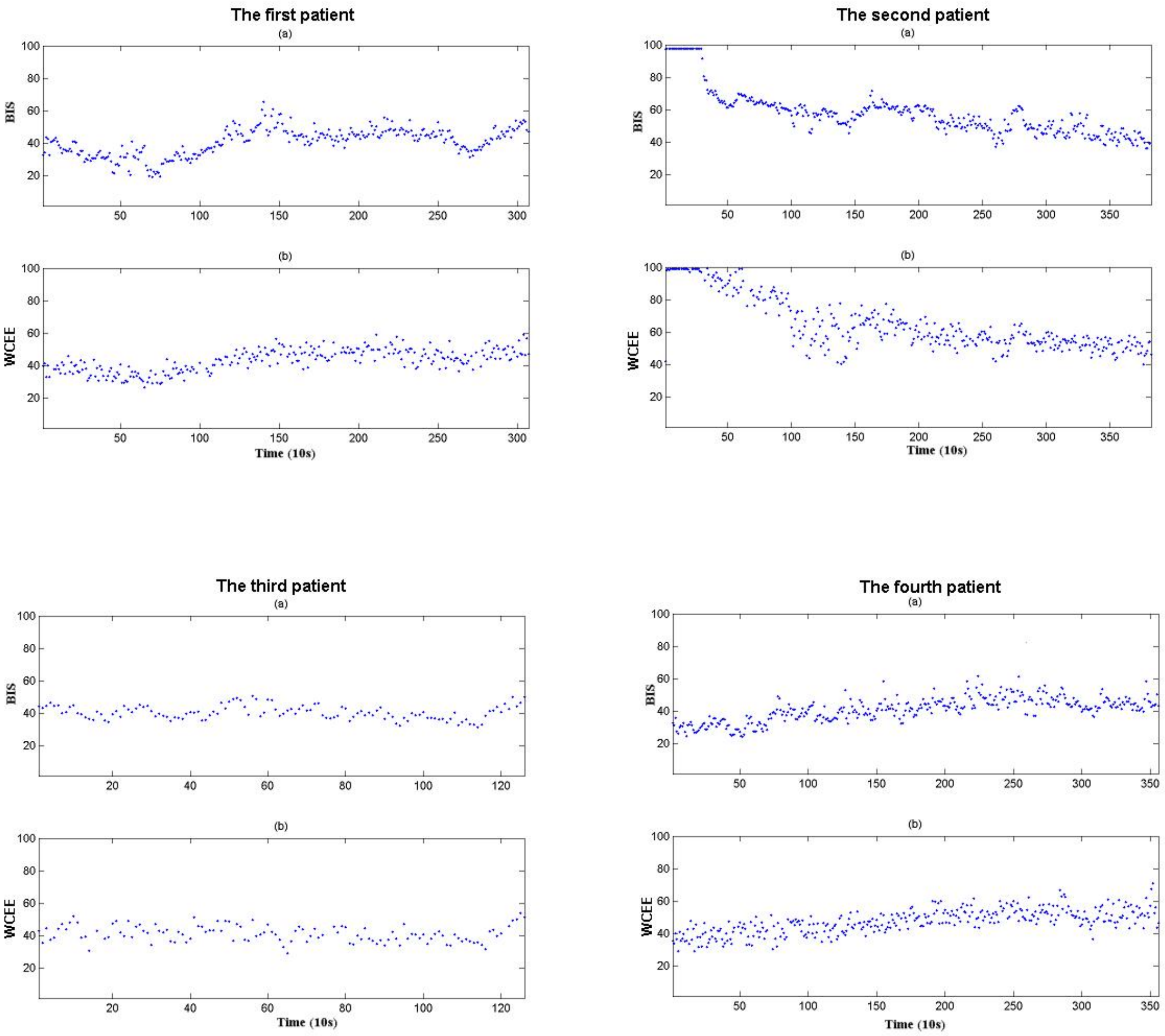


Fig. 3. In (a)s BIS index of the four persons is plotted versus time and In (b)s the results of the proposed method versus time is illustrated

with the BIS index results. Moreover, experimental results empirically showed that our method can significantly decrease the noise effect produced by artifacts produced by ECG, OAs and electrical apparatuses in the operation room. The proposed method can be applied to other EEG processing fields such as detecting the seizure through the EEG for infants or detection of imagery movements in the brain computer interface (BCI) field.

## ACKNOWLEDGMENT

The authors of this paper present their warm regards to Reza Sameni and Farid Zand for their valuable academic comments on this paper.

## REFERENCES

[1] B. A. Orser, Depth of anesthesia monitor and the frequency of intraoperative awareness, The New England Journal of Medicine, vol. 358, 2008, pp. 1189-1191.
[2] H.L. Kaul, N. Bharti, Monitoring depth of anesthesia, Indian J. Anesth., vol. 46, 2002, pp. 323-332.
[3] L. Shao-hua, W. Wei, D. Guan-nan, K. Jing-dong, H. Fang-xiao, T. Ming, Relationship between depth of anesthesia and effect-site concentration of propofol during induction with the target-controlled infusion technique in elderly patients, Chinese Medical Journal, vol. 122, 2009, pp. 935-940.
[4] P. S. Sebel, T. A. Bowdle, M. M. Ghoneim, I. J. Rampil, R. E. Padilla, T. J. Gan, and K. B. Domino, The incidence of awareness during anesthesia: A multicenter United States study, Anesth. Analgesia, vol. 99, 2004, pp. 833-839.
[5] D. R. Stanski, Monitoring depth of anesthesia, in Anesthesia, R. D. Miller, Ed. Anesthesia, (Churchill Livingstone, New York, 1994, pp. 1127-1159).
[6] E. W. Jensen, P. Lindholm, and S. Henneberg, Autoregressive modeling with exogenous input of middle-latency auditory-evoked potentials to measure rapid changes in depth of anaesthesia, Meth. Inf. Med. vol. 35, 1996, pp. 256-260.

[7] H. Litvan, E. W. Jensen, J. Galan, J. Lund, B. E. Rodriguez, S. W. Henneberg, P. Caminal, and J. M. Villar Landeira, Comparison of conventional averaged and rapid averaged, autoregressive-based extracted auditory evoked potentials for monitoring the hypnotic level during propofol induction, Anesthesiology, vol. 97, 2002, pp. 351-358.
[8] J. Rampil, A primer for EEG signal processing in anesthesia, Anesthesiology, vol. 89, 1998, pp. 981-1001.
[9] J. C. Sigl and N. G. Chamoun, An introduction to Bispectral analysis for the EEG, Journal of Clinical Monitoring and Computing Springer Netherlands, vol. 10, 1994, pp. 392-404.
[10] P.Ch. Ivanov, A.N. Amaral, Lus, A.L. Goldberger, S. Havlin, M.G. Rosenblum, Z.R. Struzik, H.E. Stanley, Multifractality in human heartbeat dynamics, Nature. vol. 399, 1999, pp. 461-465.
[11] D. Garrett, D. A. Peterson, C. W. Anderson, M. H. Thaut, Comparison of Linear, Nonlinear, and Feature Selection Methods for EEG Signal Classification, IEEE Trans. neural systems and rehabilitation engineering, vol. 11, 2003, pp. 141-144.
[12] P. Flandrin, Time-Frequency or Time-Scale Analysis, Academic Press, London, 1999.
[13] F. Hlawatsch, G.F. Boudreaux-Bartels, Linear and quadratic time-frequency signal representations, IEEE Signal Process. Mag., vol. 9, 1992, pp. 21-67.
[14] T. W. Schnider, C. F. Minto, S. L. Shafer, P. L. Gambus, C. Andresen, D. B. Goodale, and E. J. Youngs, The influence of age on propofol pharmacodynamics, Anesthesiology, vol. 90, 1999, pp. 1502-1516.
[15] S. L. Shafer and K. M. Gregg, Algorithms to rapidly achieve and maintain stable drug concentrations at the site of drug effect with a computer- controlled infusion pump, Journal of Pharmacokinetics and Pharmacodynamics, Springer, vol. 20, 1992, pp. 147-169.
[16] M. M. R. F. Struys, T. De Smet, B. Depoorter, L. F. Versichelen, E. P. Mortier, F. J. Dumortier, S. L. Shafer, and G. Rolly, Comparison of plasma compartment versus two methods for effect compartment-controlled target-controlled infusion for propofol, Anesthesiology, vol. 92, 2000, pp. 399-406.
[17] Vigon L, Saatchi M R, Mayhew J E W and Fernandes R, Quantitative evaluation of techniques for ocular artifact filtering of EEG waveforms, IEE Proceedings on Science Measurement Technology, vol. 147, n.5, Sep 2000.
[18] Girton D G, Kamiya J, A simple on-line technique for removing eye movement artifacts from the EEG, Electroencephalography and Clinical Neurophysiology, vol. 34, pp. 212-216, 1973.
[19] V. J. Samar, A. Bopardikar, R. Rao, Kenneth Swartz, Wavelet Analysis of Neuroelectric waveforms: A Conceptual Tutorial, Brain and Laguage, vol. 66, 1999, pp. 7-60.
[20] T Gasser, L Sroka and J Mocks, The transfer of EOG activity into the EEG for eyes open and closed, Electroencephalography and clinical neurophysiology, vol. 61, 1985, pp. 181-193.
[21] http://www.xploretat.de/tutorials/waveframe8.html
[22] V. krishnaveni, S. jayaraman, N. malmurugan, A. kandaswamy, K. ramadoss, Non adaptive thresholding methods for correcting ocular artifacts in EEG, academic open internet journal, vol. 13, 2004.
[23] M. Nakamura, H. Shibasaki, Elimination of EKG artifacts from EEG records: a new method of noncephalic referential EEG recording Electroencephalogr, Clin. Neurophys. vol. 66, 1987, pp. 89-92.
[24] H.J. Park, D.U. Jeong, K.S. Park, Automated detection and elimination of periodic ECG artifacts in EEG using the energy interval histogram method, IEEE Trans. Biomed. Eng. vol. 49 n.12, 2002, pp.1526-1533.
[25] N.V. Thakor, J.G. Webster, W.J. Tompkins, Estimation of QRS complex power spectra for design of a QRS filter, IEEE Trans. Biomed. Eng. vol. 31, 1984, pp. 702-705.
[26] J. A. Jiang, C. F. Chao, M. J. Chiu, R. G. Lee, C. L. Tseng, R. Lin, An automatic analysis method for detecting and eliminating ECG artifacts in EEG, Computers in Biology and Medicine, vol. 37, 2007, pp. 1660 - 1671.
[27] H. A. Al-Nashash, J. S. Paul, N. V. Thakor, Wavelet entropy Method for EEG Analysis: Application to Global Brain Injury, 1st International IEEE EMBS Conf. on Neural Engineering, Capri Island, Italy, 2003, pp. 348-351.
[28] M. Mikaili, S. Hashemi, Assesment of the complexity/regularity of transient brain waves (EEG) during sleep, based on wavelet theory and the concept of of entropy, Iranian J. of science and Technology, vol. 26, pp.639-646, 2002.
[29] O. A. Rosso, S. Blanco, A. Rabinowicz, "Wavelet analysis of generalized tonic-clonic epileptic seizures," Signal Processing, vol. 83 n.6, June 2003, pp. 1275-1289.
[30] R. Hornero, D. E. Abasolo, P. Espino, "Use of wavelet entropy to compare the EEG background activity of epileptic patients and control patients," in Proc. 7th International Symposium, vol. 2, 2003, pp. 5-8.
[31] T. Zikov, S. Bibian, G. A. Dumont, M. Huzmezan,C. R. Ries, Quantifying Cortical Activity During General Anesthesia Using Wavelet Analysis, IEEE Trans. On biomedical engineering, vol. 53, April 2006.

**Toktam Zoughi** was born in 1984. She received her B.Sc. in Computer Science, 2006. She is currently studying M.Sc. in Artificial Intelligence, in Shiraz University, Shiraz, Iran. Her research interests include biomedical signal processing and image processing.

**Reza Boostani** was born in 1973; he received his B.Sc.in Electronics from Shiraz University, Shiraz, Iran, in 1996 and his M.Sc. and Ph.D. in Biomedical Engineering from Amirkabir University of Technology, Tehran, Iran, in 1999 and 2004, respectively. He has spent his research period in Graz University of Technology in the BCI field from 2002 to 2003. Since 2004, he has been a faculty member of the Computer Science and Engineering Department of Shiraz University. His current research interests include biomedical signal processing, statistical pattern recognition and machine learning.