Indian Journal of Fundamental and Applied Life Sciences ISSN: 2231– 6345 (Online)
An Open Access, Online International Journal Available at www.cibtech.org/sp.ed/jls/2015/01/jls.htm
2015 Vol.5 (S1), pp. 330-336/Sadeghipour et al.

Research Article

CLASSIFICATION OF CEREBRAL SIGNALS IN HEALTHY INDIVIDUALS AND PATIENTS WITH EPILEPSY

***Ehsan Sadeghipour[1], Kambiz Ghaemi Osgouie[2], Ahmad Hatam[3] and Rahman Mahdizadeh[4]**
[1]*Young Researchers and Elite Club, Islamic Azad University, Bandar Abbas Branch, Bandar Abbas, Iran*
[2]*Department of Engineering, International Campus-Kish Island, University of Tehran, Tehran, Iran*
[3]*Department of Electrical and Computer Engineering, University of Hormozgan, Bandar Abbas, Iran*
[4]*Sama Technical and Vocational Training College, Islamic Azad University, Bandar Abbas Branch, Bandar Abbas, Iran*
**Author for Correspondence*

ABSTRACT

One of the most common neurologic disorders of the nervous system following a stroke is epilepsy from which approximately 0.6% to 0.8% of the world population suffers. This disease is caused by a sudden change in the potential difference between inside and outside of the neuron. World statistics indicate that 43 individuals per one hundred people get epilepsy in developed countries annually, while this number reaches 86 individuals in developing countries. EEG signal is the most important method to diagnose epilepsy. EEG records produce information with high lengths, and it takes a long time for the specialist to analyze the information in order to detect the epileptic area. In this paper, a variety of smart systems is used to perform automatic classifications in order to find epileptic EEG. The results indicate the superiority of classic XCS method in comparison with other ones.

Keywords: *EEG Signal, Epilepsy, Smart Systems, XCS*

INTRODUCTION

One of the most common neurologic disorders of the nervous system following a stroke is epilepsy from which approximately 0.6% to 0.8% of the world population suffers. World statistics indicate that 43 individuals per one hundred people get epilepsy in developed countries annually, while this number reaches 86 individuals in developing countries (Donald, 2001). This disease is caused by a sudden change in the potential difference between inside and outside of the neuron. Normally, there is an approximate potential difference of 70 to 90 microvolts, which is due to the selective pass feature of the cell membrane, between inside and outside of the cell membrane. In this case, the brain cells are well-active, so neural waves and impulses are produced at a specific intensity and regularity. But in individuals with epilepsy, the nerve cells of some brain parts leave the natural state, and the ionic balance is disrupted among different ions inside the cell. Consequently, the potential difference changes between inside and outside of the cell, and it may change from -70 to -90 toward more negative or more positive potential. As a result of changes in ionic system, the physiological performance of the cell gets disrupted and reveals different clinical reactions. The clinical reactions caused by changes in potential difference vary based on which category of cells the changes occur in. Given this definition, it can be concluded that the neurological cell type determines the clinical symptoms of epilepsy. For example, if the changes of potential occur in the motor cortex of brain cells, then motor symptoms will reveal, and if they occur in visual, auditory, or olfactory cells, there will be some disruptions in the respective parts (Orrin, 2002). Of the most important symptoms of epilepsy, we can mention the sudden and frequent occurrence of epileptic seizure which creates problems for patients and affects the quality of their lives badly because of the limitations it causes in their social lives. Sometimes it may jeopardize their lives. Epilepsy, in the first stage, emerges through the occurrence of sudden and frequent epileptic seizures in the patient. Given the type of epilepsy, the side effects and the type of seizures vary, too. The cerebral activity observed during a seizure is mainly different from the normal state of the patient in terms of frequency and neuronal pattern. It means that the time pattern of neurons changes from the normal state into the intermediate state (pre-seizure phase) gradually and enters the state of seizure then (Iasemidis *et al.*, 1994). Despite these

© Copyright 2014 | Centre for Info Bio Technology (CIBTech)

differences, the precise diagnosis of epilepsy could be difficult, because every seizure cannot be caused by epilepsy.

In order to diagnose this disease precisely, the researchers can help the doctors by designing the systems which detect its physiological and pathological deviations, by running MRI and CT SCAN tests, and also by scrutinizing EEG signals meticulously (Subasi, 2005) (Zhou *et al*., 2003). The analysis of EEG activity in diagnosing epilepsy was initiated after the rhythmically electronic activities in the scalp were recorded by Hans Burger (Pradhan, 1996). Pradhan *et al.*, used raw EEG signals as the neural network inputs for the first time. Adeli *et al.*, also categorized EEG signals into two groups of healthy and epileptic by analyzing wavelet chaos and neural networks (Adeli, 2003).

Weng *et al.*, used an adaptive network whose results revealed lesser errors in the detection of radiations induced by epileptic seizures (Weng, *et al.*, 1998). Bandt *et al.*, introduced the sequential patterns according which they proposed a new complexity measure named permutation entropy to analyze non-linear time series (Bandt, *et al.*, 2002). This measure showed good resistance against noise (Cao, *et al.*, 2004). First, we deal with signal preprocessing and noise removal of EOG, EMG, ECG, and AC frequency in this paper, and then, using the intelligent systems, we study the diagnosis of epilepsy by using the features extracted from EEG signals and by classifying the cerebral signals in healthy individuals and patients with epilepsy.

Wavelet Transform

Wavelet transform is a tool which divides data, functions or operands into different frequency components and checks each one in the respective scale precisely. Like Fourier transform, the continuous wavelet transform of a function is defined as the sum of the products of the aforementioned function times shifted and scaled wavelet function throughout the time period. It is generally as follows:

(1) $$C(\text{scale}, \text{position}) = \int_{-\infty}^{+\infty} f(t)\psi(\text{scale}, \text{position})\, dt$$

(2) $$C(a,b) = \int_{-\infty}^{+\infty} f(t)\frac{1}{\sqrt{a}}\psi\left[\frac{t-b}{a}\right] dt$$

The result of wavelet transform is the coefficient C which is a function of scale and position. The product of each of coefficient times the respective scaled and shifted wavelet determines its contribution to the main signal. The general schema of this process is shown in figure 2.

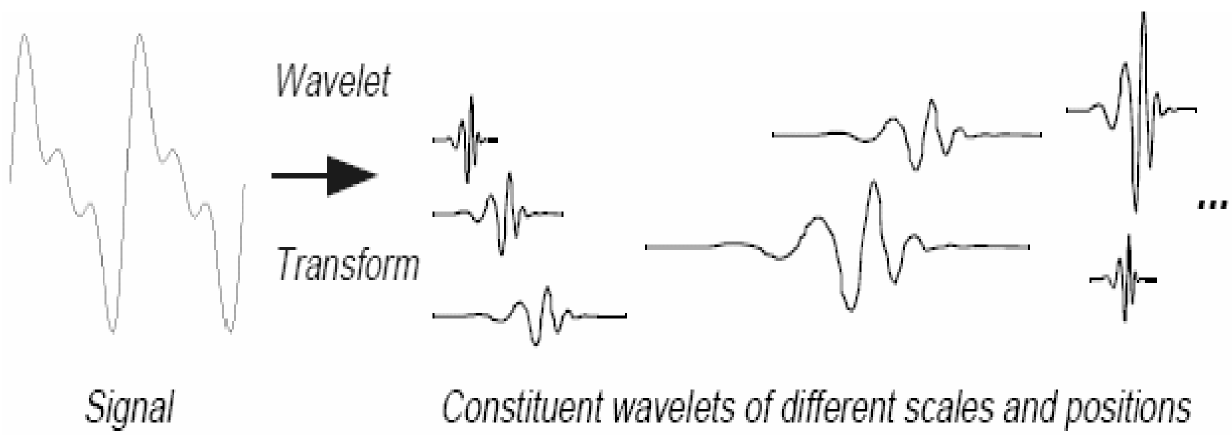

Figure 1: The General Schema of Wavelet Transform

The shift and scale which have been used in wavelet definition are simply defined according to figure 3. The shift means the movement of wavelet along the axis of time, and the scale means the extent to which wavelet is expanded along the axis of time. The domain of wavelet drops as its scale develops because its energy has to be constant.

© Copyright 2014 | Centre for Info Bio Technology (CIBTech)

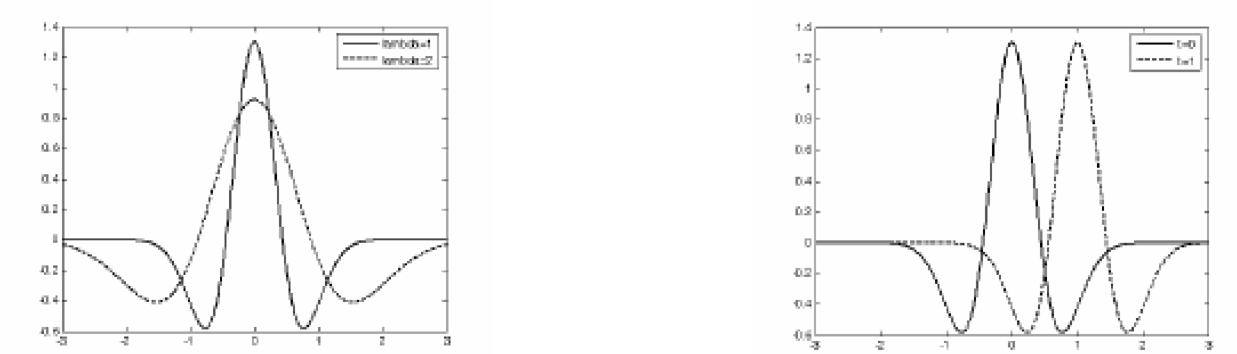

Figure 3: The Right Side of Left Shift and Scale of a Wavelet

It should be noted that the big scale of wavelet equals low frequencies, while its small scale equals high frequencies. The mean and energy of each function, which is adopted as wavelet, is zero and one unit, respectively. These concepts are stated in the following relations. Moreover, the transformed wavelet must meet the admission requirements, so the signal transmitted on the basis of wavelet would be reconstructed on a time basis.

(3) $\int_{-\infty}^{+\infty} \psi(u) du = 0$

(4) $\int_{-\infty}^{+\infty} \psi^2(u) du = 1$

(5) $0 < \int \frac{|\psi(f)|^2}{f} df < \infty$

In relation 6, we have:

(6) $\psi(f) = \int_{-\infty}^{+\infty} \psi(u) e^{-2\pi f u} du$

As the main signal was reconstructed through its Fourier transform, the signal could give back a time basis in case of the transmitted signal on the basis of wavelet.

(7) $f(t) = \frac{1}{k_v} \int \int C(a,b) \frac{1}{\sqrt{a}} \psi \left[\frac{t-b}{a}\right] \frac{da db}{a^2}$

Discrete Wavelet Transform

In order to make it easier to work with discrete wavelet transform, it is usually discretized in a binary way. It means that the scale and position are integer powers of 2.

(8) $a = 2^j, j \in Z$

(9) $b = ka, k \in Z$

Therefore, the discrete wavelet is formulated as follows:

(10) $\psi_{j,k}(t) = 2^{\frac{-j}{2}} \psi(2^{-j} t - k)$

Given equation 10 and the definition of continuous wavelet transform, the discrete wavelet transform of time series f (n) is written as follows:

(11) $C(j,k) = \sum_{n \in Z} f(n) \psi_{j,k}(n)$

In this (discrete) equation, n equals t. The reconstruction of signal can be calculated simply through the following formula and with reference to what has been mentioned so far.

(12) $f(t) = \sum_{j \in Z} \sum_{k \in Z} C(j,k) \psi_{j,k}(t)$

It is worth mentioning that it is possible to reconstruct certain parts of the signal if required. Thus, some parts of the signal can be omitted optionally. This capability is used in applications like reducing the noise of signal. What has been said is executable in the reconstructing process according to equation 13.

(13) $f_j(n) = \sum_{k \in Z} C(j,k) \psi_{j,k}(n)$

So the signal can be decomposed into components associated with each other. A signal is decomposed into two parts in wavelet transform while the low-pass decomposition is called estimation, and the high-pass decomposition is called details (figure 4).

© Copyright 2014 | Centre for Info Bio Technology (CIBTech)

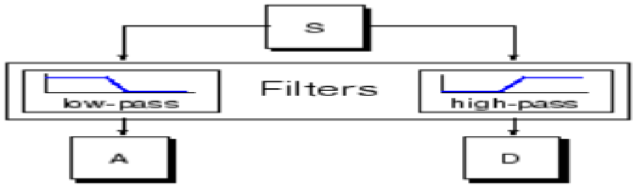

Figure 4: The Filters of Discrete Wavelet Transform

Wavelet Packet

This transform is a generalized wavelet decomposition in which the details can be decomposed like the estimations. The decomposition of a signal to the second level by using wavelet packet is shown in figure 5.

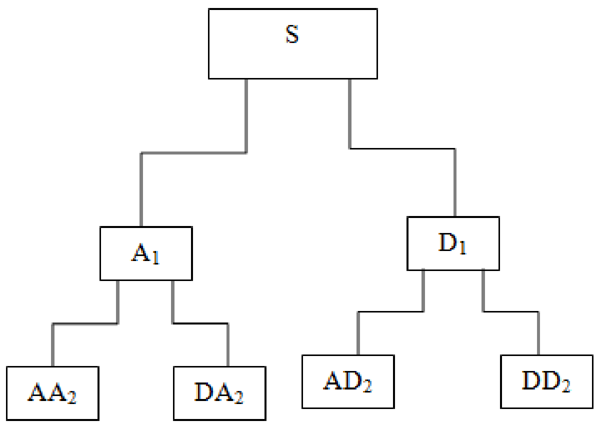

Figure 5: The Decomposition of a Signal to the Second Level by Using Wavelet Packet

For example, the signal S can be shown as AA_2+DA_2+D_1 by using wavelet packet; however, the usual wavelet is not able to express the signal in this way.

IDE Method

The problem of selecting a feature is raised in the discussion of machine learning in order to identify a pattern statistically. This problem bears a notable deal of importance in many applications like classification, because there are many features which are neither useful nor informative enough. Removing these features wouldn't create an information problem, but removing irrelevant and extra features reduces the computation load. Moreover, it makes lots of unnecessary information be stored with useful data.

This method uses an evaluating distance-based function which consists of six stages. In the first stage, the average distance is calculated among states' samples then the average distance of states is calculated. In the second stage, the variance of first stage is calculated. Then in the third stage, the average eigenvalue of each sample is calculated in each state. In the fourth stage, the average distance of states' samples is calculated. In the fifth stage, the compensation factor is calculated. Finally, the ratio of states' samples average distance to the average distance among the samples of different states is calculated and normalized then. Therefore, the most efficient features can be chosen out of the set of features based on distance from the greatest value to the smallest one.

Different Classification Methods for Diagnosis

Adaptive Neuro Fuzzy Inference System or Adaptive Network-Based Fuzzy Inference System (ANFIS)

The fuzzy system is a system based on fuzzy if-then regulations and is not analyzable with classic probability theories. The objective of fuzzy logic is to extract the precise results by using a set of regulations which has been defined by specialists. However, the neural networks are capable of learning and teaching. Using the observed data, they can determine network parameters in a way that the desired output is achieved in return of an arbitrary input. Yet, the neural networks are not capable to use human knowledge and to make inference by using lingual expressions in a way that fuzzy systems can. Therefore, a type of fuzzy neural networks named ANFIS was proposed in 1999 in order to achieve the learning ability of neural networks and the inference features of fuzzy systems in model TSK. Bearing the learning ability of neural networks and the inference power of fuzzy systems, ANFIS can find every type of non-linear mapping or model in order to coordinate the inputs and the outputs precisely. Thus, ANFIS is a multi-layered neural network based on fuzzy systems whose structure is shown in figure 6. All nodes are adaptive in the first layer whose output is the fuzzy membership degree of inputs.

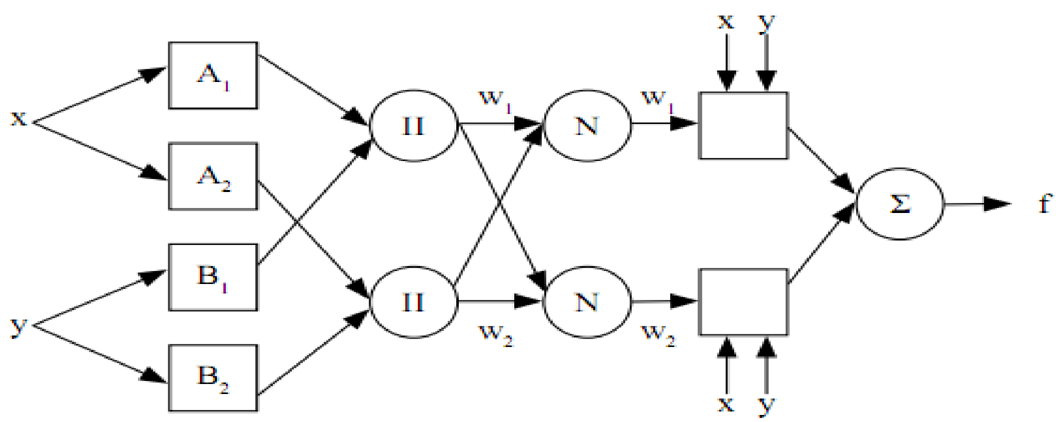

Figure 6: ANFIS

The Learning System XCS

Machine learning refers to a wide range of supervised and unsupervised leaning algorithms, and its objective, in data mining, is to avoid exhaustive search for data and to replace this time-consuming type of searching with smart methods which make it possible to classify and model the behavior of data easily by finding the patterns existing within data. Many approaches have been proposed in data mining for the last two decades, and various algorithms of supervised, unsupervised or reinforcement types are used in them for purposes such as pattern detection and allocation. Classifier systems could be pointed out as one of the most successful methods.

Generally, the classifier systems include a set of if-then regulations, one of which proposes a potential solution for the target problem. Becoming updated with the help of a genetic algorithm in particular intervals, this set of regulations is gradually evaluated by using a reinforcement learning mechanism. The system learns environment’s behavior during this gradual evolution, and, in the application phase, it gives appropriate responses to the queries raised by users.

The first classifier system named LCS (Learning Classifier System) was proposed by Holand in 1976. In this system, the value of each regulation was assessed through an index named strength. The strength of a regulation was increased according to its accountability for the educational examples under the conditions of learning, and an evolutionary search algorithm (usually a genetic one) took the responsibility for making new regulations and omitting inefficient ones in specific intervals. At the end of the education stage, this set of regulations is relatively able to present acceptable solutions for new queries. Yet, the successful performance of LCS depends on the selection of appropriate values for control parameters of system, a fact which was mainly depended on system designer’s experience.

Other types of classifier systems have been proposed since the emergence of LCS. The Extended Classifier Systems (XCS) is one of them. The ability of these systems was so limited in finding appropriate responses before the presentation of XCS in 1995. However, they have gradually become smarter and more precise since then, and it is now believed that XCS and its enhanced versions are able to solve complicated problems without needing to adjust the parameters. After introducing a classifier

© Copyright 2014 | Centre for Info Bio Technology (CIBTech)

Research Article

system with continuous variables (XCSR), some natural shortcomings of binary classifier systems like failure to report the specific value ranges of variables got resolved noticeably, and these systems are known as one of the most successful learning agents to solve data mining problems in partially observable environments nowadays.

The Classification Algorithm SVM

This algorithm is a supervised learning method which is used for classification and regression. It is a relatively new method which has shown better classification performance rather than the old ones. The classifier SVM works based on the linear classification of data, and it is advisable to choose a line with a wider margin of safety in linear division of data. QP methods which are known in solving limited problems are used to solve the equation of finding the optimal line for data. The data ought to be moved to a space with higher dimensions by using φ functions before linear division so that the machine can classify highly-complicated data. The equation 14 is the meta-page data-classifying relation. The equations 15 and 16 are parallel meta-page relations based on the conditions of maximum margin. The distance between two marginal pages is equal to $\frac{2}{||w||}$ if these simple functions are drawn.

(14) $w \times x - b = 0$
(15) $w \times x - b = -1$
(16) $w \times x - b = 1$

X is the input variable while w is the normal line-dividing vector, and b is the y-intercept of the separator line.

Methodology

A set of data which has been collected by diagnosing patients with epilepsy includes different specifications whose one group has been formed only in accordance with laboratory data. The data bank of the Department of Epilepsy in Bonn University is one of the most validated data bases on EEG. These data report disruptions in encephalogram signal after an epileptic seizure in a group of five patients. The signals have been studied in the groups including waking volunteers with their eyes opened, waking volunteers with their eyes closed, two states including the activities in intervals between seizures, and the final state including activities during seizures. The above-mentioned data relates to temporal lobe epilepsy, and each set includes 100 segments of single-channel EEG as long as 23.6 seconds which has been sampled at frequency 173.61. Each file has been divided into 10-second time slices decomposed up to level 10 by using wavelet transform, and the specifications of entropy, power, energy, variance, standard deviation, and mean have been extracted for each level. Therefore, 60 specifications have been extracted. The threshold of algorithm IDE must be considered 0.6 in order to choose a specification. Therefore, only 6 specifications had greater values than the threshold among 60 presented specifications:

1- The standard deviation of signal (ADA3)
2- The energy of signal (ADDAADA7)
3- The variance of signal (ADAADA6)
4- The power of signal (DADA4)
5- The power of signal (ADAADAA7)
6- The standard deviation of signal (AADA4)

Then these six specifications were added to various classification methods to acquire the accountability percentage and computational cost. To put the results of tests in identical conditions at the time of performing the calculations, a computer operating on a CPU of 2.4 GHz and 4 GB of RAM has been used in all tests. As it is seen in table 1-1, the computational cost of method SVM is smaller than that of all the above-mentioned methods, while method XCS is the best one in terms of validity.

Methodology	Computational Cost in Minutes	Percentage of Correct Answers
SVM	3	85.3%
KNN	2	92.4%
XCS	6	97.8%

CONCLUSION

In this paper, the use of classier systems has been proposed in order to diagnose patients with epilepsy among healthy individuals by considering clinical symptoms. To do so, data pertaining to 5 individuals have been extracted from one of the most validated data bases on EEG, then 6 specifications of wavelet transform's coefficients have been applied to different classification methods by using algorithm IDE. The results indicated that XCS method had higher precision and a greater rate of convergence in comparison with other common data-mining methods.

REFERENCES

Adeli H and Zhou Z *et al.*, (2003). Analysis of EEG records in an epileptic patient using wavelet transform. *Journal of Neuroscience Methods* **123** 69-87.

Adeli H, Dadmeher N and Ghosh-Dastidar S (2007). Mixed-Band wavelet-chaos-neural network methodology for epilepsy and epileptic seizure detection. *IEEE Transaction on Biomedical Engineering* **54**(9) 827-833.

Bandt C and Pompe B (2002). Permutation entropy- a natural complexity measure for time series. *Physical Review Letters* **88**(17) 174102.

Cao Y, Tung W, Gao J, Protopopescu V and Hively M (2004). Detecting dynamical changes in time series using the permutation entropy. *Physical Review E* **70** 046217.

Donald Weaver (2001). *Epilepsy and Seizures: Everything You Need to Know* (Firefly Books).

Iasemidis LD, Olson LD, Sackellares JC and Savit RS (1994). Time dependencies in the occurrences of epileptic seizures: A nonlinear approach. *Epilepsy Research* **17** 81-94.

Lopes da Silva FH, Pijn JP and Wadman WJ (1994). Dynamics of local neuronal networks: Control parameters and state bifurcations in epileptogenesis. *Progress in Brain Research* **102** 359-370.

Orrin Devinsky (2002). *Epilepsy: Patient and Family Guide*, 2nd edition (F.A. Davis Company).

Pradhan N, Sadasivan PK and Arunodaya GR (1996). Detection of seizure activity in EEG by an artificial neural network. a preliminary study. *Computers and Biomedical Research* **29**(4) 303-313.

Subasi A (2005). Epileptic seizure detection using dynamic wavelet network. *Expert Systems with Applications* **29** 343-355.

Subasi A and Gursoy MI (2010). EEG signal classification using PCA, ICA, LDA and support vector machines. *Expert Systems with Applications* **37** 8659-8666.

Weng W and Khorasani K (1996). An adaptive structure neural network with application to EEG automatic seizure detection. *Neural Network* 1223-1240.

© Copyright 2014 | Centre for Info Bio Technology (CIBTech)