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Detection of Epileptic Activity In The Human EEG-Based Wavelet Transforms and SVM

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Abstract

Epilepsy is a chronic neurological disorder which is identified by successive unexpected seizures. Electroencephalogram (EEG) is the electrical signal of brain which contains valuable information about its normal or epileptic activity. In this work EEG and its frequency sub-bands have been analyzed to detect epileptic seizures. A discrete wavelet transform (DWT) has been applied to decompose the EEG into its sub bands. Statistical features Energy, Covariance are calculated for each sub-band. The extracted features are applied to Feed Forward Neural Network For system for classifications got classification accuracy of 98%.

Keywords: Electroencephalogram (EEG) signals, Epilepsy, Seizures, Epileptic Seizures, discrete wavelet transform, feed forward neural network (FFNN)

1.Introduction:

Epilepsy is one of the world's most common neurological diseases, affecting more than 40 million people worldwide. Epilepsy's hallmark symptom, seizures, can have a broad spectrum of debilitating medical and social consequences [1]. Although antiepileptic drugs have helped treat millions of patients, roughly a third of all patients are unresponsive to pharmacological intervention. Understanding of this dynamic disease evolves; new possibilities for treatment are emerging. An area of great interest is the development of devices that incorporate algorithms capable of detecting early onset of seizures or even predicting those hours before they occur. This lead time will allow for new types of interventional treatment. In the near future a patient's seizure may be detected and aborted before physical manifestations begin. Electroencephalogram (EEG) has established itself as an important means of identifying and analyzing epileptic seizure activity in humans. In most cases, identification of the epileptic EEG signal is done manually by skilled professionals, who are small in number [2]. The diagnosis of an abnormal activity of the brain functionality is a vital issue. EEG signals involve a great deal of information about the function of the brain. But classification and evaluation of these signals are limited. Since there is no definite criterion evaluated by the experts, visual analysis of EEG signals in time domain may be insufficient. Routine clinical diagnosis needs to analysis of EEG signals. Therefore, some automation and computer techniques have been used for this aim. Recent applications of the wavelet transform (WT) and feed- forward neural network (FFNN) to engineering-medical problems can be found in several studies that refer primarily on the signal processing and classification in different medical area. WT applied for EEG signal analyses and FFNN applied for classification of EEG signals is not a new concept. Several papers in different ways applied WT to analyze EEG signals and combine the WT and NN in the process of classification. Some of the papers are listed in the references [2]-[27]. This paper presents an algorithm for classification of EEG signals based on wavelet transformation (WT) and patterns recognize techniques. Discrete Wavelet Transform (DWT)) is applied to decompose EEG signal at resolution levels of the components of the EEG signal (δ, θ, α, β and γ) and the Parseval's theorem are employed to extract the percentage distribution of energy features of the EEG signal at different resolution levels. The feed-forward neural network (FFNN) classifies these extracted features to identify the EEGs type according to the percentage distribution of energy features. The paper is organized as follow. The method of the proposed process is presented in Section II of this paper. Test results of classifications are given in Section III. Conclusions are given in Section IV.

2. Materials And Methods

2.1 Depiction of the EEG Database

The datasets used in this research are selected from the Epilepsy center in Bonn, Germany by Ralph Andrzejak [28]. The data consists of five groups, free EEG signals both in normal subjects and epileptic patients. The first two groups are recorded from five healthy subjects: with open (A) and closed eyes (B). The third and fourth groups are recorded prior to a seizure from part of the brain with the epilepsy syndrome (C) and from the opposite (healthy) hemisphere of the brain (D). The fifth group (E) is recorded from part of the brain with the epilepsy syndrome during the seizure. Three sets denoted A, C and E is used in this work. Each set contains 100 single channel EEG segments of 23.6-sec duration at a sampling rate of fs = 173.61 Hz. Set A consisted of segments taken from surface EEG recordings that were obtained from five healthy volunteers using a standardized electrode placement. Set E only contained seizure activity.

2.2. Wavelet Decomposition:

Wavelet Transform The wavelet transform (WT) introduces a useful representation of a function in the time-frequency domain [29-32]. Basically, a wavelet is a function $\psi \in L^2$ (R) with a zero average

$\int \Psi(t)dt = 0$ ------------------------------------- (1)

The DWT is defined by using discrete values of the scaling parameter *a* and the translation parameter *b* . To do so, set $a = a_0^m$ and $b = nb_0 a_0^m$, then we get $\Psi_{m,n}$ (t)-$a_0^{-m/2}$ $\Psi(a_0^{-m}$ t-$nb_0)$, where m, $n \in Z$, and m is indicating frequency localization and n is indicating time localization. Generally, we can choose $a0 = 2$ and $b0 = 1$. This choice will define a dyadic-orthonormal WT and provide the basis for multi-resolution analysis (MRA). In MRA, any time series $x(t)$ can be completely decomposed in terms of approximations, provided by scaling functions $\varphi\ m\ (t)$ (also called father wavelet) and the details, provided by the wavelets$\psi\ m\ (t)$. The scaling function is associated with the low-pass filters (LPF), and the wavelet function is associated with the high-pass filters (HPF). The decomposition procedure starts by passing a signal through these filters. The approximations are the low-frequency components of the time series and the details are the high-frequency components. The signal is passed through a HPF and a LPF. Then, the outputs from both filters are decimated by 2 to obtain the detail coefficients and the approximation coefficients at level 1 (A1 and D1). The approximation coefficients are then sent to the second stage to repeat the procedure. Finally, the signal is decomposed at the expected level. According to Parseval's theorem, the energy of the distorted signal can be partitioned at different resolution levels.
Mathematically this can be presented as:

$EDi = \sum_{j=1}^{N} |Dij|^{\,2},\ i = 1, \ldots\ldots, l$ -- (2)

$EA_i \ = \sum_{j=1}^{N} |A_{ij}|^2$ ---------- (3)

where i =1,......,l is the wavelet decomposition level from level 1 to level l. N is the number of the coefficients of detail or approximate at each decomposition level. *EDi* is the energy of the detail at decomposition level i and *EAl* is the energy of the approximate at decomposition level l.

2.3 Artificial Neural Networks

Artificial neural networks (ANNs) are formed of cells simulating the low-level functions of biological neurons. In ANN, knowledge about the problem is distributed in neurons and connections weights of links between neurons [15]. The neural network must be trained to adjust the connection weights and biases in order to produce the desired mapping. At the training stage, the feature vectors are applied as input to the network and the network adjusts its variable parameters, the weights and biases, to capture the relationship between the input patterns and outputs. ANNs are particularly useful for complex pattern recognition and classification tasks. ANNs are widely used in the biomedical field for modeling, data analysis and diagnostic classification. There are many different types and architectures of neural networks varying fundamentally in the way they learn, the details of which are well documented in the literature [33-35].

3. Proposed Method:

The EEG signal contains a several spectral components. The amplitude of a human surface EEG signal is in the range of 10 to 100 μV. The frequency range of the EEG has a fuzzy lower and upper limit, but the most important frequencies from the physiological viewpoint lie in the range of 0.1 to 30 Hz. The standard EEG clinical bands are the delta (0.1 to 3.5 Hz), theta (4 to 7.5 Hz), alpha (8 to 13 Hz), and beta (14 to 30 Hz) bands [1]. EEG signals with frequencies greater than 30 Hz are called gamma waves. The datasets used in this research are selected from the Epilepsy center in Bonn, Germany by Ralph Andrzejak [32]. The data consists of five groups, free EEG signals both in normal subjects and epileptic patients. The first two groups are recorded from five healthy subjects: with open (i) and closed eyes (ii). The third and fourth groups are recorded prior to a seizure from part of the brain with the epilepsy syndrome (iii) and from the opposite (healthy) hemisphere of the brain (iv). The fifth group (v) is recorded from part of the brain with the epilepsy syndrome during the seizure. Three sets denoted A, C and E is used in this work. Each set contains 100 single channel EEG segments of 23.6-sec duration at a sampling rate of fs = 173.61 Hz. Set A consisted of segments taken from surface EEG recordings that were obtained from five healthy volunteers using a standardized electrode placement. Set E only contained seizure activity.

The object of wavelet analysis is to decompose signals into several frequency bands. Selection of appropriate wavelet and the number of decomposition levels are very important for the analysis of signals using DWT. The number of decomposition levels is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal that correlate well with the frequencies necessary for classification of the signal are retained in the wavelet coefficients. In this work, Daubechies 4 (db4) is selected because its smoothing feature was suitable for detecting changes of the EEG signals. Daubechies wavelets are the most popular wavelets representing foundations of wavelet signal processing, and are used in numerous applications. A detailed discussion about the characteristics of these wavelet functions can be found in the reference [14].The decomposed signals are shown in figure 1.

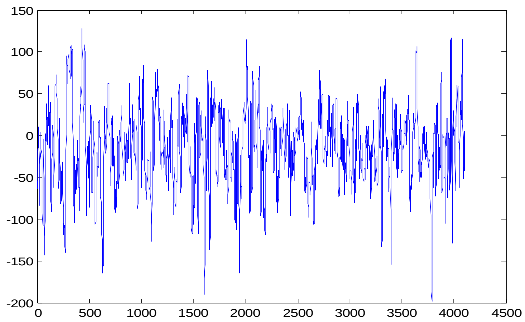


Fig 1.a

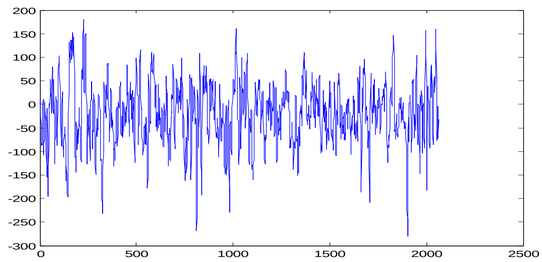


Fig 1.b

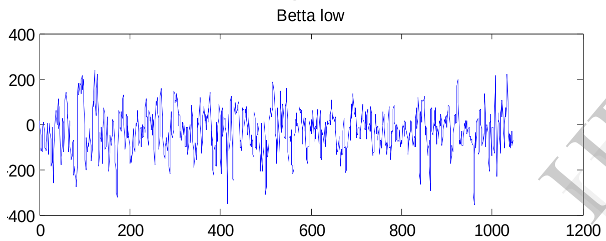


Fig 1.c

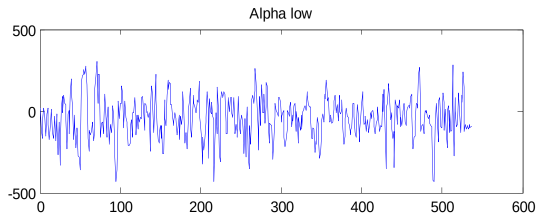


Fig 1.d

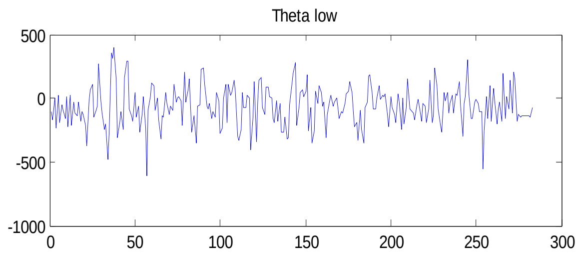


Fig 1.e

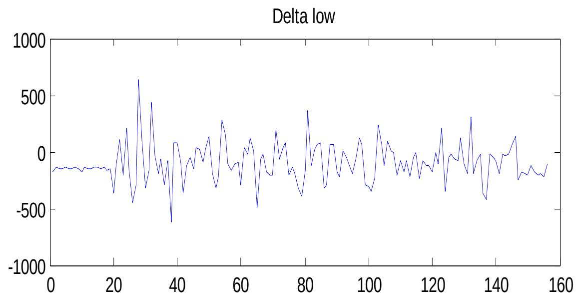


Fig 1.f

(“**Fig1**.**Represents different decomposed signals**”)

Classification of EEG signals requires the use of pattern recognition techniques. Pattern recognition is a process of perceiving a pattern of a given object based on the knowledge already possessed [33]. So automated pattern recognition uses various artificial intelligence techniques like fuzzy logic (FL), artificial neural networks (ANN) and adaptive fuzzy logic (AFL) for the classification of disturbance signals. Recently, techniques based on probabilistic models like Hidden Markov models, Dynamic time wrapping, Dempster-Shafer theory of evidence are also proposed. An algorithm block diagram for classification of EEG signals is presented on Fig. 2. The algorithm structure is based on two stages: feature extraction stage (FES) and classification stage (CS). The input of the CS is a preprocessed signal. In this case, EEG signal in the time domain is transformed into the wavelet domain before applying as input to the CS. Feature extraction is the key for pattern recognition. A feature extractor should reduce the pattern vector (i.e., the original waveform) to a lower dimension, which contains most of the useful information from the original vector. In this algorithm, after realizing the FES (preprocessing), using detail and approximation coefficients in each decomposition level obtained from WT, the CS (processing) is implemented by using neural network (NN). NN are good at tasks such as pattern-matching and classification.

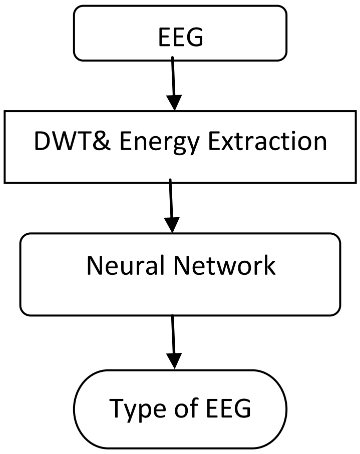
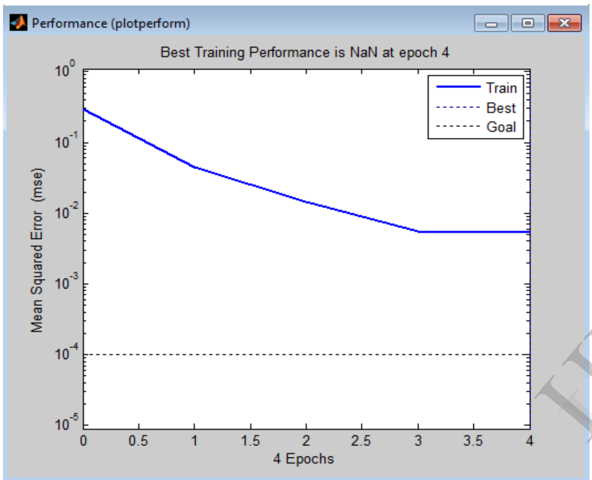


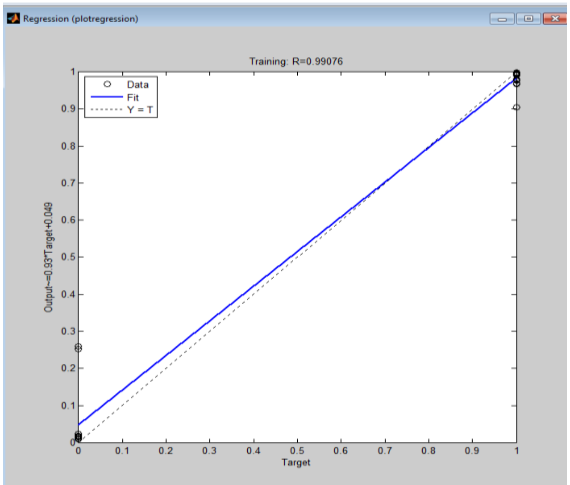
Fig 2. Block diagram for classification of EEG.

3.1 CLASSIFICATION RESULTS:

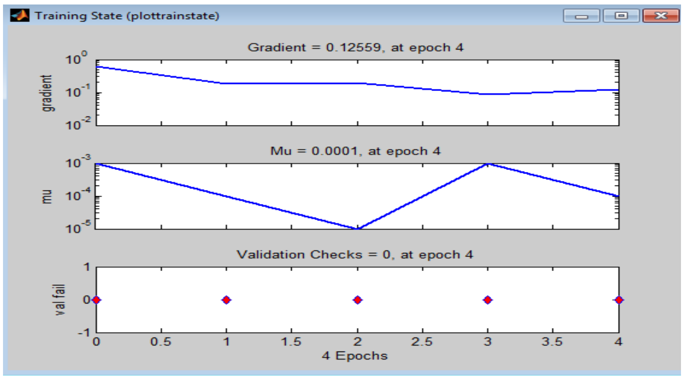
In the classification stage, the proposed wavelet energy distribution features are applied as input to NN. NN is a powerful pattern recognition tool. It is defined as software algorithms that can be trained to learn the relationships that exist between input and output data, including nonlinear relationships Support Vector Machine (SVM) is used to classify different EEG signals. The extracted feature vectors are classified using a SVM classifier. The SVM is a discriminative model classification technique that mainly relies on two assumptions. First, transforming data into a high-dimensional space may convert complex classification problems (with complex decision surfaces) into simpler problems that can use linear discriminate functions. Second, SVMs utilize only those training patterns that are near the decision surface assuming they provide the most useful information for classification [36].



"Fig.3.aProgress performance of SVM classifier"

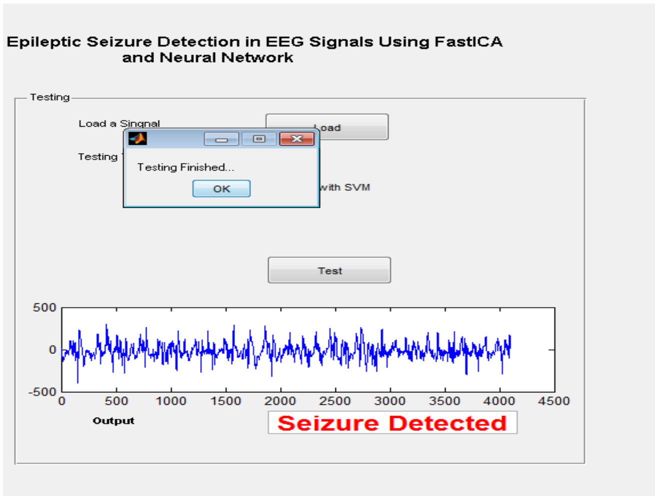


"Fig 3.c Regression rate of SVM classifier"



"Fig 3.b Training state progress of SVM classifier"

Classification consists of two steps – training and testing. The leave-one-out cross-validation method is used to assess the performance of the system for patient-independent seizure detection [37]. This way, all but one patients' data is used for training and the remaining patient's data is used for testing. This procedure is repeated until each patient has been a test subject and the mean result is reported. The leave-one-out method is known to be an almost unbiased estimation of the true generalization error; that is, the performance reported with the leave-one-out method is the most similar to the performance this system would show on an unseen test dataset of infinite length once it is trained on all available data. The output of the algorithm is shown in Fig 4.



"Figure 4. Output of the algorithm"

The classified accuracy rate of the EEG signals of the proposed approach was 96.0%. Hundred percent correct classification rates are obtained for normal EEG signals. In Table I presented are classification results of DWT and SVM algorithm

Table I

EEG CLASSIFICATION RESULTS OF DWT with SVM algorithm

Normal - Correct Predicted	20 out of 20
Normal - Wrong Predicted	0 out of 20
Attack - Correct Predicted	19 out of 21
Attack - Wrong Predicted	2 out of 21

4. Conclusion:

Epileptic seizures are manifestations of epilepsy. The detection of epileptiform discharges in the EEG is an important component in the diagnosis of epilepsy. As EEG signals are non-stationary, the conventional method of frequency analysis is not highly successful in diagnostic classification. In this paper we have presented a novel approach to detect seizures based on a set of diverse feature, which capture energy of the EEG signal using DWT, and a statistical machine learning algorithm – SVM – to derive a data-driven non-linear function to discriminate between seizure and non-seizure. The system showed the best performance (up to this date) of a neonatal seizure detection system. The proposed SVM-based seizure detection system allows for control of the final decision by choosing different confidence levels which makes the proposed system flexible for clinical needs. The results showed that the proposed classifier has the ability of recognizing and classifying EEG signals efficiently. The most important advantage of the proposed method is the reduction of data size as well indicating and recognizing the main characteristics of signal.

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