DTCWT Based EEG Classification Using ANN and Statistical Feature Analysis for Brain Diseases Diagnosis

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Abstract— This paper is presented to propose an automatic support system for EEG signal classification to brain diseases diagnosis or epilepsy seizure detection. The signal classification is a challenging problem due to its complexity. The Artificial Neural Network is used for classification of EEG signal. If we go through the manual analysis of EEG signals it may become time consuming or inaccurate and also it will require a trained person for the diagnosis. Decision making is done in two steps that are feature extraction in DTCWT domain and classification using artificial neural network. The artificial neural network has implemented the multilayer perceptron neural network and back propagation network. By using BPN we get the fast and accurate classification. The performance of BPN has evaluated in terms of training performance and classification accuracy.

Key words: Dual Tree Complex Wavelet Transform(DTCWT), Artificial Neural Network(ANN), Back Propagation Network (BPN)

I. INTRODUCTION

About 40 to 50 million people in the world are suffering from a neurological disorder known as epilepsy. The epilepsies are chronic neurological disorder in which cluster of nerve cells or neurons in the brain sometimes signal abnormally and causes seizure. Neurons normally generate chemical and electrical signals that act on other neurons or glands to produce human thoughts, feeling and actions. During epilepsy this signals becomes 500 times much faster than normal. Detection of epilepsy or seizure attack is carry out by viewing EEG records. An automatic seizure detection system reduces a noticeable number of volumes of data to be observed. The purpose of the system is to relieve the neurologist off the burden of time consuming bulky data observation by providing alarms and also to reduce the effect of misinterpretation by manual seizure detection that is highly subjective. Such a system can integrated into an implantable device to make detecting the onset of seizures and for that trigger an alarm and initiate treatment by neurostimulation or drug delivery. It’s proved that double reading of medical images improves the result for brain disease diagnosis or epilepsy detection. Hence for this automated classification of EEG signals by using an already prepared set of data like intensity and some anatomical feature is proposed. Brain computer interfaces (BCI) provides the communication between the human and the system by using brain signals. The signal classification module is composed of the obtained EEG signal feature extraction and the transformation of these signals into device instructions. The EEG classification technique depends on the incentive and thereby the reaction to detect all the events related with it like motor imagery or slow cortical potentials. The predicted EEG drives the classification to some precise feature extraction methods.

Therefore an objective of this paper the EEG brain signal has classified to distinguish normal and abnormal behaviour of signal with better accuracy that is given by Double Tree Complex Wavelet Transform (DTCWT). Here the back propagation has applied to the system with feed forward for classification which follows the supervised training and non-knowledge based classification. The test samples are classified by ANN using network parameters and it’s features.

II. EEG SIGNAL DISCREPTION

An EEG signal is a recording of electrical activity of the brain from the scalp. EEG activities are very small so the signal intensity measured in microvolts (mV). Main frequencies of human brain waves can be categorize as Delta, Theta, Alpha, and Beta. Variables which used for the classification of EEG activities are Frequency, Voltage, Morphology, Synchrony and Periodicity. The standardized placement of scalp electrodes for an EEG recording is 10/20 system. The distance in percentages of the 10/20 range between Nasion-Inion and fixed points is the key point of this system. In this paper the publicly available database has been used for the further analysis and classification purposes. These datasets are analyzed sets of EEG time series. These sets contains the surface EEG recording from healthy volunteers with eyes closed and eyes open and some recordings are intracranial from epilepsy patients during the seizure free interval from within and from outside the seizure generating area and also the intracranial EEG recordings of epileptic seizure. The standard 10-20 scalp electrode method used to record the data. These recordings gives five sets of grouped data namely A, B, C, D, E. Set A and B contained segments recorded from surface EEG recording that carried out on five healthy volunteers at relaxed state with eyes open and eyes closed by using a standardized electrode placement scheme. Set C, D and E has taken from volunteers selected for EEG recordings; all had achieved complete seizure control after resection of one of the hippocampal formations by same scheme, which was therefore correctly diagnosed to be the epileptogenic zone. Each group contains 100 single channel EEG segments of 23.6 sec. Duration. All the recordings have done with the 128-channel amplifier system. 12-bit Analog-to-digital conversion done and with that the data were written continuously onto the disk of a data acquisition computer system at sampling rate 173.61 Hz. Hence the sample length of each segment has become $173.61 \times 23.6 \approx 4097$. In this paper we have used four grouped dataset namely Z, O, F, S. Each contains 90 EEG segments.

III. FEATURE EXTRACTION IN DTCWT DOMAIN

The dataset has recorded with lowpass filtering. The range of frequency for EEG signal spans over 0-60Hz.Hence frequency over 60Hz has removed considered as noise. For the analysis of EEG signal the band limited signal has subjected to 4-level decomposition. The forward transform of DTCWT contains two branches containing real and imaginary coefficients. For the analysis the EEG signal the band limited signal has subjected to 4-level decomposition. After the first level of decomposition the EEG signal decomposed into its higher resolution component tde11(30-60Hz) and lower resolution component tde21(0-30Hz). Now, in the second level for decomposition, the tde21 has decomposed into higher resolution component, tde 211(15-30Hz) and lower resolution component, tde221(0-15Hz). So, the component we get after four level of decomposition gives five components. As each component has two parts, real and imaginary, each frequency band gives total four real and four imaginary coefficient hence the 4-level decomposition gives ten Subbands in total(i.e. five for real and five for imaginary. And by using inverse DTCWT the reconstruction of these components approximately correspond to the physiological EEG sub-bands delta, theta, alpha and beta respectively.

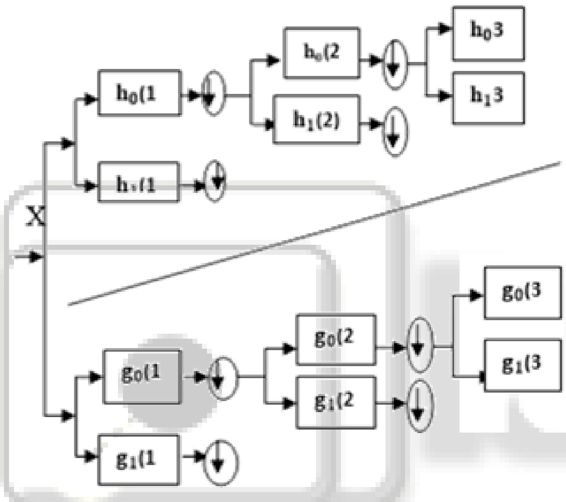

Fig. 1: Block diagram of DTCWT

The construction of each level of tree has provided a set of data points to get the result at finer level. Mean, Variance, Standard Deviation, Entropy, Skewness and Kurtosis are intensity based features that are extracted from segmented regions are those parameters.

Mean (μ) is simply the average of the objects in consideration. Mean of the region is found out by adding all the pixel values of the region divided by the number of pixels in the region.

Variance (σ^2) measures how far a set of pixels of the image are spread out. A variance of zero indicates that all the values are identical.

$$\sigma^2 = E(x^2) - (E(x))^2 \quad \ldots(1)$$

Standard deviation (σ) is the square root of the variance. It also measures the amount of variation from the average. A low standard deviation indicates that the data points tend to be very close to the mean.

Entropy (en) it is a statistical measure of randomness that can be used to characterize the texture of the input image.

$$en = -\sum_x \sum_y p(x,y) \log p(x,y) \quad \ldots(2)$$

Skewness (sk) is asymmetry in a statistical distribution, in which the curve appears distorted or skewed either to the left or to the right. Skewness can be quantified to define the extent to which a distribution differs from a normal distribution.

$$\beta 1=\frac{1}{N}\sum_{i=1}^{N}\left(\frac{x-\mu}{\sigma}\right)^3 \quad \ldots(3)$$

Signal	F	O	S	Z
Me	2.489	1.602	12.165	3.775
Mi	144.405	158.30	1.4286e+003	957.3481
Mx	172.062	185.0057	1.341e+003	1.19e+003
Sd	39.0971	46.5856	405.6307	393.1819
Va	1.5286	2.1702	164.5363	154.5920
Ent	1.1325	1.128	1.0095	0.9955
Sk	0.1150	0.0046	0.3152	0.3063

Table 1: Statistical Parameters

IV. METHOD

We have used the Levenberg-Marquadt algorithm as neural network tool box. For the single real input x and network function F the derivative F'(i) is computed in two phases: feed forward and back propagation. The steps used in back propagation algorithm are: (1)feed forward computation (2)Back propagation to the output layer (3)backpropagation to the hidden layer (4)Weight updates. DTREG is used for removing the unnecessary neurons. By leave-one-out validation method the least error increasing neurons has removed from the model. The dataset has divided into training, validation and test subsets. The training stopped after 3 iterations. For the analysis of performance of the network response we put entire dataset through the network and it will perform a linear regression between the network outputs and the corresponding target.

The whole experiment is carried out by MATLAB 7.8.0(R2009a), OS-Microsoft Windows7, 64-bit platform having 4GB RAM.

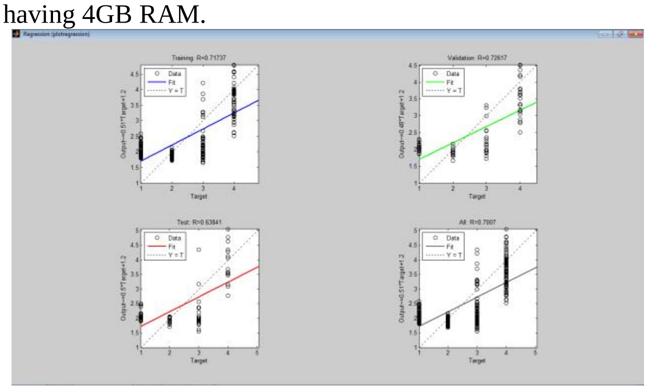

Fig. 2:

V. RESULT

Hence to get the patients real states we went through a procedure in that we took some publicly available EEG data sets. We used 360 samples for the training data set and 36 samples for testing. 9 segment in each class of dataset. The training data set used to train the Multilayer perceptron neural network and with testing data set we have verified the accuracy and observed the effectiveness of the trained network for EEG classification. The analysis of EEG signal has done in the DTCWT domain. To distinguish these bands some parameters has used those are variance, standard deviation and skewness. For each classification problem we have created four different training data sets with 90 samples in each data set. And the training and classification has done with ANN network using Levenberg-Marquardt algorithm. Table 1 shows the performance evaluation parameter.

For the performance analysis of classifier the parameters are evaluated as:

Sensitivity: Tp. / (Tp + Fn)

Specificity: Tn./(Fp + Tn)

Accuracy: (Tp+Tn)./(Tp+Tn+Fp+Fn)

We achieved the performance metrics as, Sensitivity: 94.44%, Specificity: 88.88% and Accuracy: 91.66%.

VI. CONCLUSION

For achieving all this performance, the EEG database has analyzed and we went through a procedure with best system architectures. For EEG signal analysis we used DTCWT domain. By using DTCWT domain we obtained shift invariance, directional selectivity, perfect reconstruction and limited redundancy; these are the significant property providing by DTCWT. Feature extraction of signals has done on the basis of different parameters namely mean, variance, standard deviation, entropy and skewness. These are the measurement of central tendency and it helps to calculate the nature of the signal for classification processes or it can be known as pre-classification. For training and classification, we used back propagation network and the Multilayer perceptron neural network. BPN is a fastest neural network for the gradient computation for non-linear multilayer networks. The regression performance is the best way to perform the classification. We achieved a satisfactorily accuracy with 91.66% and this is best performance with DTCWT and ANN till now.

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