AUTOMATED CLASSIFICATION OF EEG SIGNALS USING DTCWT AND ANN CLASSIFIER

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Abstract: This work deals with classification of brain signals which are employed in various scientific and practical fields such as Medical Science, Cognitive Science, Neuroscience and Brain Computer Interfaces. Brain signal analysis experiences complex challenges such as small sample size, high dimensionality and noisy signals. The detection of Electroencephalogram (EEG) brain signals in patients to distinguish between normal and abnormal signals which are tumor and epilepsy is highly essential. Therefore a very demanding process is required for detailed analysis of the entire length of the EEG data. In this paper, automated classification of EEG signals for the detection of normal and abnormal activities using Dual-tree Complex Wavelet transform (DTCWT) and Artificial Neural Network (ANN) Classifier is considered. Feature extracted from input EEG signals and the performance of the proposed algorithm is simulated. The results showed that the proposed classifier has the ability of classifying EEG signals efficiently.

Keywords: Brain Computer Interfaces (BCI), DTCWT, ANN, EEG.

1. Introduction

A. Brain Computer Interfaces

Brain–Computer Interfaces (BCI) is the best feasible way of providing the communication between the human and the system by means of brain signals. By using this BCI the patients can put across their views or needs by means of their brain signals just by thinking process. The signal classification module is composed of the obtained EEG signal features extraction and the transformation of these signals into device instructions. The EEG classification tactic depends on the inducement and, thereby, the reaction to detect motor imagery, event related potentials, slow cortical potentials, or steady-state evoked potentials. The predicted EEG drives the classification to some precise feature extraction methods.

The presence of electrical activity in the brain was detected for the first time in 1875 by Caton. In 1929, Berger did a study to prove this claim. Berger, revealed the presence of electrical activity in the human brain. He realized that with the help of electrodes placed on the head and a galvanometer connected to these electrodes. Then, Berger observed that these signals called EEG are changed with the opening and closing of the eyes. With these developments, the presence of EEG signals was scientifically proved. In 1934, Adrian and Matthews ensured of strengthening and recording of EEG signals obtained with the electrodes. The number of research dealing with this issue has increased day by day with the impact of the big developments in the field of electronics and computer. Today, EEG signals are used in many areas, such as diagnosis of epilepsy, controlling of anesthesia stage in surgical operations, and determining the depth of anesthesia, sleep disorders, investigation of sleep psychology, and diagnosis of migraine. Brain–computer interface is used to measure the EEG signals. The first part of this interface is metal electrodes, which are used for measuring the electrical activity of the brain from the head surface. Generally, measurements are made according to an electrode placement scheme called the international 10–20 system. EEG signals have very low amplitude (in μv levels) values. To be able to interpret these signs, they should be amplified by EEG device. This amplified EEG signal is drawn on a paper in continuous form. The recorded EEG signals are similar to the multichannel seismograph record. Evaluation of EEG recordings is performed by neurologists who specialized in this subject. The five main wave types in EEG signals are: alpha (8–13 Hz), beta (13–30 Hz), delta (0–4 Hz), gamma (30–100+ Hz), and theta (4–7 Hz). EEG signals are not periodic and their amplitude, phase, and frequencies change continuously.

Therefore, these signals are very difficult to interpret. EEG data are visually analyzed by neurologists. This process is rather stressful and tiresome. Also, EEG signals analyzed by neurologists who have received different
training may generate inconsistent information. Therefore, it is imperative to analyze EEG signals with a consistent and suitable method in order to ensure correct epilepsy diagnosis and treatment. The purpose of this study is to identify an algorithm with better classification accuracy than existing algorithms, and to ensure the provision of gradable information through the use of EEGs.

2. Related Works

An investigation of recent studies shows that various different models have been suggested to assist neurologists in identifying epileptic activities. Some of the studies with high classification accuracies are provided below. A direct comparison of our study to those of others reported in the recent literature in terms of classification accuracy is also given in the form of a table in the result section of this paper.

In [1] two-layered learning vector quantization network is used in order to analyze EEG signals. In [2] EEG signals are applied to recurrent neural networks instead of applying them to statistical properties in the identification of epileptic seizures. In extracting features from EEG signals used five features based on time and frequency [3]. High accuracy rates were obtained in the system, where Elman recurrent neural network was used as a classifier.

In [4] two feature values are used to express relative spike amplitude and spike occurrence frequency. A multistage nonlinear preprocessing filter was used to extract these features. Later, these features were used as input data, especially for artificial neural networks (ANNs).

In this connection, MLPNN (Multilayer Perceptron Neural Network) and logistic regression models are used in the identification of epileptic seizures in the analysis of EEG signals [5]. In another study, [6] compared the two outputs (normal and epileptic) MLPNN, and used a mixture of expert model in the classification of EEG data.

In [7], 92% classification accuracy is obtained by using different entropy values and an Adaptive Neuro Fuzzy Inference System (ANFIS) algorithm. In [8], chaotic measures are used in the identification of features from EEG signals. These measures included correlation dimension, the largest Lyapunov exponent, Hurst exponent, and entropy values. The authors arrived at a classification accuracy of higher than 90%.

Polat and Gunes proposed a hybrid model containing decision tree (DT) algorithms and a fast Fourier transformation base. In [9] variety of higher order spectral (HOS) attributes are used to distinguish normal and practical EEG signals, and they also indicated unique ranges for these features for various classes with high confidence level (p-value of less than 0.05).

In [10], authors obtained features from EEG signals by relative wavelet energy (RWE) algorithm in different frequency bands. A classification accuracy of 95.2% was obtained in the system, where ANN was used as a classifier.

In their studies, they obtained eight real-valued attribute values from EEG data. They turned these attribute values into four attribute values in the form of complex numbers. The resulting four complex-valued attribute values are presented as an introduction to a complex-valued neural network (CVANN). The parameter values of the CVANN were obtained by trial and-error. The results indicate that high accuracy values were obtained.

3. Proposed Method

The diagnosis structure presents to categorize the EEG brain signal of patient to differentiate between usual and unusual which are tumor and epilepsy with improved classification accuracy. Here, the system uses the back propagation with feed forward for classification which follows the supervised training and non-knowledge based classification. For cross validation training, the statistical principal features will be extracted with help of data base samples. The test sample will be classified using network parameters and its features. The system gives better performance accuracy for different test samples.

Dual-tree Complex wavelet transform provides advantages over the continuous wavelet transform as

- Applicable for multiple signals for abnormal detection in a short time.
- No loss of details due to shift variant property.
- Easy to get accurate results.
- It will give information about at which time it happens.
Methodologies:

- Input EEG Signals
- Pre-processing
- DTCWT (Dual-tree Complex Wavelet transform)
- Feature extraction
- ANN Classification

A. Input EEG Signals

Electroencephalography (EEG) is an electrophysiological monitoring process to trace electrical action of the brain. It is typically noninvasive, with the electrodes placed along the scalp, although invasive electrodes are sometimes used in specific applications. EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain.

EEG biofeedback or neuro feedback uses EEG signal for feedback input. It is suggested that this learning procedure may help a subject to modify his or her brainwave activity.

B. Pre-processing

Pre processing helps to enhance the quality of an image by removing the unwanted noise, illumination and contrast. The unwanted noise is removed by using a median filter. Median filter is a non-linear filter with a good denoising power and computational efficiency. Median filter suppress the impulse noise at the expense of blurring the image. These filters are applied across all the pixels of the image irrespective of whether the pixels are good or corrupted.

C. DTCWT (Dual-tree Complex Wavelet transform)

Dual-tree Complex wavelet transform (CWT) provides advantages over the critically sampled CWT for signal and image processing. The dual-tree CWT is implemented as two separate two-channel filter banks. To gain the advantages described in this example, you cannot arbitrarily choose the scaling and wavelet filters used in the two trees.

Dual-tree complex wavelet transformation (DTCWT) has been applied in various levels for feature extraction and statistical features are obtained from the obtained complex-valued feature vector. Discrete wavelet transformation (DWT) has a wide range of applications, and is frequently used in many fields, such as signal and image compression, feature extraction, noise reduction, channel coding, image processing, and the numerical solution of partial differential equations.

Although it offers a proficient computational algorithm and limited representation, the DWT displays four fundamental disadvantages compared to DTCWT.

1) Shift sensitivity

If there is an unpredictable change in transformation coefficients when there is a shift (change) in the time for the input signal, this transformation is defined based on shift sensitivity. Shift sensitivity is an unwanted characteristic. DWT coefficients are unsuccessful in differentiating the input-signal changes. DTCWT is insensitive to change. When compared with standard DWT, it has a developed sensitivity toward shifts in time.

2) Poor directionality

Standard DWT is unsuccessful in selecting diagonal characteristics. DTCWT has 12 wavelets (six for the real tree and six for the imaginary tree) in two dimensions oriented in $\pm 15^\circ$, $\pm 45^\circ$, and $\pm 75^\circ$.

3) Absence of phase information

DWT algorithm, important shortcoming is phase information absence. All natural signals are mainly real-valued and therefore complex valued filtering is necessary in order to benefit from local phase information. As opposed to normal wavelet transform (WT), the DT-CWT algorithm uses complex functions instead of real valued main wavelet functions. This way, amplitude and phase information can be examined separately.
4) The DTCWT uses analytic filters to perform the wavelet analysis. DTCWT has a more complex structure compared to standard DWT, and is composed of two DWTs that work parallel to each other, as shown in Fig. 1. One of these trees is called the real tree, whereas the other is called the imaginary tree.

D. Feature extraction

After obtaining the noise-free signals from the signal enhancement phase, essential features from the brain signals were extracted. For feature extraction from EEG signals use methods like Adaptive Auto Regressive parameters (AAR), bilinear AAR, multivariate AAR, Fast Fourier Transformations (FFT), PCA, ICA, Genetic Algorithms (GA), Wavelet Transformations (WT), Wavelet Packet Decomposition (WPD). The most commonly used feature extraction techniques are ICA, PCA, WT, AR, WPD and FFT.

4. Simulation Results

The proposed feature set is embedded in a pattern recognition framework where we have used ANNs for classification purposes we have used a publicly available EEG dataset for our experiments. Several classification objectives can be effectively studied using this dataset. We have considered thirty different cases, referring to different objectives from a clinical perspective. Our experiments have shown that in two cases which indicate a three-class pattern recognition problem, we get significant performance improvements after the use of hybrid features for the extraction of important data from the EEG signals. Under our test setup, the proposed technique expands the classification performance by more than 10% for the (when using an ANN classifier) as compared to the respective benchmark methods for these cases.

The performance of this method is studied using standard measures such as Sensitivity (Sn), Specificity (Sp) and Accuracy (Acc), expressed as

\[ Sn = \frac{TP}{TP+FN} \times 100\% \]
\[ Sp = \frac{TN}{TN+FP} \times 100\% \]
\[ Acc = \frac{(TP+TN)}{(TP+TN+FP+FN)} \times 100\% \]

Where TP, TN, FP and FN stands for true positive, true negative, false positive and false negative. For all the cases, it produces as Sensitivity = 83.33%, Specificity = 100% and Accuracy = 90%.

5. Conclusion

In this work, we have proposed a method for the classification of EEG brain signal of a patient by distinguishing between normal and abnormal which are tumor and Epilepsy with Artificial Neural Network Classifier with the better accuracy of about 90% which is more when compared to other classifiers.

In future, we expect to expand this work by researching on the likelihood to extract more discriminative components to additionally enhance the classification.
results. Furthermore, we intend to investigate the likelihood to do the hardware implementation of the proposed highlights for planning a programmed seizure recognition framework for effective usage by the patients.

References


