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EEG signal classification using PSO trained RBF neural network for epilepsy identification

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ABSTRACT

The electroencephalogram (EEG) is a low amplitude signal generated in the brain, as a result of information flow during the communication of several neurons. Hence, careful analysis of these signals could be useful in understanding many human brain disorder diseases. One such disease topic is epileptic seizure identification, which can be identified via a classification process of the EEG signal after preprocessing with the discrete wavelet transform (DWT). To classify the EEG signal, we used a radial basis function neural network (RBFNN). As shown herein, the network can be trained to optimize the mean square error (MSE) by using a modified particle swarm optimization (PSO) algorithm. The key idea behind the modification of PSO is to introduce a method to overcome the problem of slow searching in and around the global optimum solution. The effectiveness of this procedure was verified by an experimental analysis on a benchmark dataset which is publicly available. The result of our experimental analysis revealed that the improvement in the algorithm is significant with respect to RBF trained by gradient descent and canonical PSO. Here, two classes of EEG signals were considered: the first being an epileptic and the other being non-epileptic. The proposed method produced a maximum accuracy of 99% as compared to the other techniques.

1. Introduction

Electroencephalography [1] is the signal generated in the brain due to the communication of a large number of neurons among each other. This collision usually generates a very small quantity of electrical signal. Hence, Electroencephalography [1] measures this electrical activity to examine the human behavior. Careful analysis of these signals contribute to the detection of many disorders where approximately 1% of the entire world population are touched by this disease. Thus, it is necessary to identify and properly diagnose the disease. If a person has a seizure, it does not necessarily mean that the person is affected by epilepsy [2]. Hence, it is really difficult to detect and differentiate between epileptic seizures and others by manual visual inspection.

There are various methods available to record the EEG signal, such as, a 10–20 electrode placement scheme to measure the EEG. In this scheme there are several electrodes placed on the human scalp to record the EEG activity. The electrodes are placed in a 10–20 international standard, where these electrical activities in a human brain are recorded by the instrumentation connected to these electrodes via cabling.

Generally, doctors take a printed copy of this recorded signal and identify whether there is any sign of epilepsy or not. But this is quite difficult for differentiating between normal seizures and epileptic seizure through normal eyes. Hence, it is necessary to get such a system in which we can analyze the EEG signal [3] and properly differentiate between normal and epileptic seizure [4]. For our work, we have used MATLAB to analyze the EEG signals. According to the survey, it is clearly taken in that, the discrete wavelet transform (DWT) is the most effective method for analyzing the EEG signals. This method generally fits into the problem where the signals are very ephemeral in nature i.e. the frequency of signal changes rapidly with respect to time [5]. Subsequently, from the analysis of EEG signals by DWT [6,7] we can discover several statistical features that can be utilized for further processing.

After analysis of the signal, the most important phase is to classify the signals as epileptic seizures or normal. Classification is considered as a fundamental task in the field of data mining. In this method, identification of the specific data sample is made as to which pre-specified group it belongs to. Here, in this problem, we have specified two groups, one is normal and the other is an epileptic seizure group. Classification of seizures in EEG signal is usually considered as one of

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the challenging tasks. In classification, we are given a set of instances consisting of several features or attributes called as training set. One of the attribute called the classifying attribute identifies the class to which each instance belongs. Some other mark of unknown instances called as testing set is used for evaluating the efficiency of classifier model.

Over many years NN have been very widely used in many biomedical signal analysis because they split the signals efficiently for decision making. Every classification system must be provided with a set of sample data that is represented by features extracted from a signal. Whereas, methods used for this, can be frequency domain features, wavelet transform, etc. Over the years there are several other architectures of NN model [8] that have been used such as Multilayer Perceptron Neural Network (MLPNN), Adaptive Neuro-Fuzzy Inference System (ANFIS), Radial Basis Function (RBF), Recurrent Neural Network (RNN), etc. Our classification method is based on RBFNNs which is itself a popular method practiced in many research fields because of its features, such as universal approximation, compact topology and faster learning speed.

The fundamental constraint in any classification method is its learning process. For any machine learning approach it is really important to choose the best learning method for classification. In our previous work [8], we had concluded that the RBFNN model required a better learning procedure for classification of EEG signals. Thus, in this paper, a modified version of the PSO algorithm is used to train the RBF network for classification of the EEG signal for epileptic seizure identification.

1.1. Related work

There are many researchers, who have proposed a number of methods to increase the performance of RBFNN in different applications. But in the application of EEG signal classification it is a whole new area. Several modified training methods have been suggested as provided below.

Vahid Fathi et al.[9] have proposed a novel PSO-OSD algorithm to improve the RBF learning algorithm in real time applications. Mazurowski et al.[10] have proposed a method for NN training and compared the same with back-propagation algorithm for medical decision making. Zhang et al.[11] have proposed a hybrid PSO-BP algorithm for training feed-forward NN. Ge et al.[12] suggested a modified PSO algorithm for training recurrent neural network.

Zhao .[13] have proposed a modified PSO algorithm called as CRPSO to train the NN for time series prediction. Guerra et al.[14] have proposed a novel method to train RBFNN using PSO and *k*-means clustering technique.

From these surveys, it is clearly understood that lot of research work have been done by researchers for performance enhancement of NN using PSO algorithm along with some variants of PSO. The remaining sections of this paper have been organized as follows. In Section 2, we have discussed the background details regarding the research work. Section 3, provides details about our proposed method for RBFNN training using IPSO. Section 4 describes the experimental detail used for the research work with the outcomes of experiments. At last, the paper concludes with its conclusion and future scopes.

2. Preliminaries

For our work, we have collected two different data samples of EEG. One is the EEG data for epileptic seizure identification from [15]. And, the other is an EEG data for eye state prediction. In the first phase of this problem, we can analyze the signal using DWT, which can provide several statistical features. These features can be used to construct a well defined dataset of samples and features.

2.1. Basics of discrete wavelet transform

Basically, all types of signals generated under medical diagnosis are analyzed in time domain with their amplitudes. Like EEG and ECG signals are generally collection of amplitudes with respect to time. If we plot this data it can give a shape from which the pathological condition of a patient can be observed. If there is any significant deviation in shape it can be shown and observed properly by visualizing the graph [16]. The same can be achieved by using any transformation technique such as Fourier Transform. But the major disadvantage of this is, it is not so effective for transient signals such as EEG. Hence, we need some other transform technique such as Wavelet Transformation for the analysis of EEG signal [16]. The basic idea behind this technique is to use a scale for analysis. This wavelet transform can be split up into two categories like Continuous Wavelet Transform (CWT), and DWT [17]. CWT was first made as an alternative to Short Time Fourier Transform (STFT). In this, the product of the signal with a role that is wavelet function is calculated [18]. This transformation is then calculated for different time domain. It is defined as given in Eq. (1).

$$\mathrm{CWT}(\mathrm{a,b}) = \int_{-\infty}^{\infty} x(t).\varphi_{\mathrm{a,b}}^{\nabla}(t)\mathrm{d}t \tag{1}$$

where $x(t)$ represents the original signal. *a, b* represents the scaling factor and translation along the time axis respectively. The symbol ∇denotes the complex conjugation and $\varphi_{\mathrm{a,b}}^{\nabla}$is calculated by scaling the wavelet at time b and scale a.

$$\varphi_{\mathrm{a,b}}(t) = \frac{1}{\sqrt{|a|}}\varphi\left(\frac{t-b}{a}\right) \tag{2}$$

where $\varphi_{\mathrm{a,b}}(t)$represents the mother wavelet. In CWT, it is assumed that the scaling and translation parameter a and b change continuously. But the main disadvantage of CWT is the calculation of wavelet coefficients [18] for every possible scale can result in a large amount of data. It can overcome with the help of DWT. It analyzes the signal at a different frequency band by decomposing the signal into a set of high and low pass filters called as Approximation and Detailed coefficients. These coefficients can be calculated by using the wavelet toolbox available in MATLAB. Using the predefined functions available inside this toolbox, we can easily extract the features of EEG signal (as shown in Figs. 1–3). For these experimental work from the data available at [15], a rectangular window of length 256 discrete data were selected to form a single EEG segment. The wavelet coefficients have been computed using Daubechies of order four.

2.2. Feature extraction

From the data available at [15], a rectangular window of length 256 discrete data were selected to form a single EEG segment. The wavelet coefficients have been computed using Daubechies of order four. This technique was found to be more suitable because of its smoothing features which are more appropriate to detect changes in EEG signal. For our study, the original signal have been decomposed as four detailed coefficients (d1, d2, d3, d4) and four approximation coefficients (a1, a2, a3, a4). For simplicity, all the approximation coefficients are ignored except the one in the last step i.e. a_4. Hence, the signal is decomposed into five segments by using DWT. In this work, for four detailed coefficients we get 247 coefficients (129+66+34+18) and eighteen for approximation coefficients. Several statistical features have been extracted. But for this study, four important features were taken into considerations:

I. Maximum of wavelet coefficients in each sub-band.
II. Minimum of wavelet coefficients in each sub-band.
III. Mean of wavelet coefficients in each sub-band.
IV. Standard deviation of wavelet coefficients in each sub-band.

Therefore, for five coefficients all total twenty features have