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A real time experimental setup for classification of epilepsy risk levels

R. Harikumar [a], T. Vijayakumar [b,*]

[a] Department of ECE, Bannari Amman Institute of Technology, Sathyamangalam, India
[b] Department of IT, Bannari Amman Institute of Technology, Sathyamangalam, India

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ABSTRACT

The objective of this paper is to analyze the performance of singular value decomposition, expectation maximization, and Elman Neural Networks in optimization of code converter outputs in the classification of epilepsy risk levels from EEG (electroencephalogram) signals. The signal parameters such as the total number of positive and negative peaks, spikes and sharp waves, their duration etc., were extracted using morphological operators and wavelet transforms. Code converters were considered as a level one classifier. Code converters were found to have a performance index and quality value of 33.26 and 12.74, respectively, which is low. Consequently, for the EEG signals of 20 patients, the post classifiers were applied across 3 epochs of 16 channels. After having made a comparative study of different architectures, SVD was found to be the best post classifier as it marked a performance index of 89.48 and a quality value of 20.62. Elman neural network also exhibits good performance metrics than SVD in the morphological operator based feature extraction method.

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1. Introduction

EEG is widely used clinical procedure for the study and diagnosis of several neurological disorders—epilepsy being one [1]. Epilepsy can be defined as a common and diverse set of brain disorders characterized by seizures. Epileptic seizures result from abnormal, excessive, and/or hyper synchronous neural activity which is characterized by a rhythmic or repetitive neural activity in the central nervous [2].

In the past, interpretation of the EEG signals were limited to visual inspection by neurophysiologist, an individual trained to qualitatively make a distinction between normal EEG activity and abnormalities contained within EEG records. EEG is characterized by repetitive high-amplitude activity, either by slow waves, or spike and wave complexes [3]. This activity varies depending upon the type of epilepsy. EEG is a determinative factor as far as patients' clinical records is concerned [4]. A common form of recording used for this purpose is an ambulatory recording that contains EEG data for a very long duration of even up to one week. It involves an expert's efforts in analyzing the entire length of the EEG recordings to detect traces of epilepsy [4].

Brain control interface (BCI) can also be considered in this context since it is a tool for direct communication between human and external devices [2]. Many BCI's make use of EEG signals to categorize two or more classes and associate them to simple computer commands. But, classification of EEG signals is a difficult task because this can only measure blurred cortical activities due to the diffusion of the skull and the skin [3]. Recordings are also highly contaminated by the noise of various sources. Therefore, while considering the EEG signals, it is important to consider both spatial and temporal dynamics of EEG data.

1.1. Motivation

Studies say that the average human brain weighs about 1.5 kg and it contains as many as 93 billion neurons and 112 billion non-neuronal cells [12]. Each of these neuron cells is in turn interconnected with each other through more than ten thousand

Abbreviations: ANN, Artificial Neural Network; AIRS, Artificial Immune Recognition System; ANFIS, adaptive neuro-fuzzy inference system; APEN, approximate entropy; AWGN, additive white Gaussian noise; BCI, brain control interface; C, scaling constant; $\varphi^*(t)$, complex conjugate of the wavelet $\varphi(t)$; CO, close–open; EEG, electroencephalogram; EM, expectation maximization; FA, false alarm; MC, missed classification; MEm, modified expectation maximization; OC, open–close; PC, perfect classification; P_{dct}, percentage of perfect classification; P_{msd}, percentage of perfect risk level missed; PI, performance index; R_{fa}, false alarm per set; $rxy(m)$, cross correlation function; SVD, singular value decomposition; S_e, sensitivity; S_p, specificity; T_{dly}, average delay of on-set classification.

* Corresponding author. Tel.: +91 9965214777.
E-mail addresses: harikumarrajaguru@gmail.com (R. Harikumar), vishal_16278@yahoo.co.in (T. Vijayakumar).

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synapses, thereby making the activity of human brain profoundly complex.

Second after stroke, epilepsy seizure is being regarded as the world's most suffered neurological disorder. It is estimated that around 50 million people worldwide suffer from this disease [5]. In many cases, there is not always a trained doctor or a neurologist on hand to take care of the patient. The staggering number of patients diagnosed with this disease illustrates the paramount importance of a better diagnosis system to improve the quality of the lives of patients.

By analyzing the biomedical signals recorded from EEG, the doctors gain a better understanding about the medical conditions of a patient before undergoing a surgery. However, it is almost impossible for electroencephalographers to scrutinize all the generated signals that have been recorded. In this regard, it is vital for an expert system to be designed and developed so that these automated classifiers not only save medical expenditure but can also speed up doctors' pre-surgical evaluations. Chang, and Vasilakos [30] introduces new types of molecular algorithms for biological computing which is a new area of improvement in the bio medical sciences and bio informatics. As shown in Refs. [30–34] a new emerging technology has been developed to enhance the understanding of the neurological computation from the quantum computing point of view.

1.2. Statement of the problem

We, in this paper, try to propose a post classifier with a high rate of performance index, with good quality value, and a low value of false alarm towards the classification of epilepsy risk levels from the EEG signals. For the comparative study purpose, we have taken into account singular value decomposition (SVD), expectation maximization (EM), modified expectation maximization (MEM) and Elman Neural Network as post classifiers. The paper begins with a brief about Electroencephanogram (EEG) and epilepsy seizures. Section 2 describes about the raw EEG data divided into 16 channels across 3 epochs for 20 patients fed as input and the samples, in turn features are realized using wavelet transforms and morphological operators. The following section then talk about the use of the code converter as a pre classifier where a set of patterns are formed (a string of alphabets). Due to the low quality, performance and nonlinearities found, we proceed with the realization of the signals with the post classifier described under Sections 6, 7 and 8. Consequently, the results are presented in tabular formats with some necessary discussions under Section 9. Eventually, the conclusion for the same is drawn from the results section.

2. Materials and methods

2.1. Electroencephanogram (EEG)

For the comparative study and to analyze the performance of the pre and post classifiers we have obtained the raw EEG data of 20 epileptic patients in European Data Format (EDF) who were under treatment in the Neurology Department of Sri Ramakrishna Hospital. An issue that has been given great attention is the preprocessing stage of the EEG signals because it is important to use the best technique to extract the useful information embedded in the non-stationary biomedical signals.

2.2. Data acquisition

The obtained EEG records were continuous for about 30 s, each of them were divided into epochs of 2-s duration. A 2-s epoch is long enough to detect any significant changes in activity and presence of artifacts and also short enough to avoid any redundancy in the signal [6].

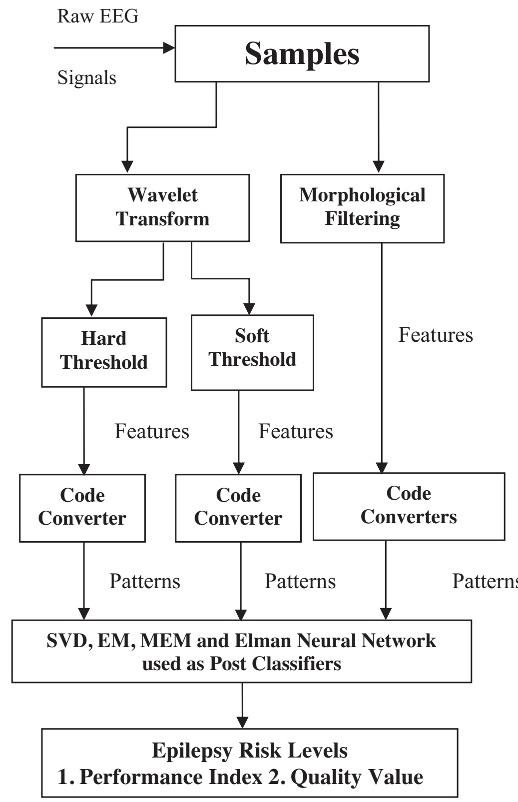

Fig. 1. Flow diagram for epilepsy risk level classification system.

For a patient we have 16 channels over three epochs. Having a frequency of 50 Hz, each epoch was sampled at a frequency of 200 Hz [13]. Each sample corresponds to the instantaneous amplitude values of the signal, totaling to 400 values for an epoch.

Fig. 1 shows the model of flow diagram of epilepsy risk level classification system. In order to classify the risk level of the patients, certain parameters were chosen which are detailed below:

For every epoch, the energy is calculated as [7]

$$E = \sum_{i=1}^{n} x_i^2 \tag{1}$$

where x_i is the signal sample value, n is the number of such samples. After having computed we go for the variance σ^2 given by

$$\sigma^2 = \frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n} \tag{2}$$

where μ is the average amplitude of the epoch. For the average variance, the covariance of duration is determined by using the equation below:

$$\mathrm{CD} = \frac{\sum_{i=1}^{p}(D - t_i)^2}{pD^2} \tag{3}$$

The following four parameters are extracted using morphological operators and wavelet transforms.

1. The total number of positive and negative peaks are found.
2. For a zero crossing function, if it is lies between 20–70 ms, then spikes are detected. If the zero crossing function lies between 70–200 ms then sharp waves are detected.
3. After having detected, the total number of spikes and sharp waves are determined as the events.

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