EPILEPTIC SEIZURE PREDICTION BY IMPLEMENTING WEIGHTED SUM OF CLASSIFIERS OUTPUT AND CONTROL BY VAGUS NERVE STIMULATION

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Abstract: Millions of people in the world suffer from epilepsy but no prediction and control system currently exists. A device that could predict a seizure and notify the patient of the impending event or trigger an antiepileptic device would dramatically increase the quality of life for those patients. This paper addresses online prediction of Epileptic seizure by analyzing EEG data and controlling it using Vagus nerve Stimulation (VNS). This proposal involves the design of a prediction system that provides with increased reliability and reduced false prediction rate by combining 3 different classifiers and making a decision based upon it. After the prediction of seizure, a VNS device is triggered, which helps in reducing the magnitude of seizure.

Index terms: Epilepsy, VNS device, seizure, Electroencephalogram(EEG).

I. INTRODUCTION

Epilepsy is one of the most common neurological disorders, with a prevalence of 0.6–0.8% of the world’s population [1]. Two-thirds of the patients achieve sufficient seizure control from anticonvulsive medication, and another 8–10% could benefit from surgery. For the remaining 25% of patients, no sufficient treatment is currently available [2]. A difficult aspect of epilepsy is the unpredictable nature of seizures. Many epileptics live in constant worry that a seizure could strike at an inopportune time resulting in humiliation, social stigma, and injury. Therefore, an implantable device that could predict a seizure by even a few seconds could dramatically change the lives of these patients by alerting them to the impending seizure or triggering a device to abate or suppress the seizure. As yet, however, there is no device or algorithm that provides sufficient power of prediction [3], [4].

The reason that seizure prediction with high sensitivity and specificity has been difficult to achieve may be the approach itself; thus, we choose an alternative classification approach. Most of the approaches to seizure prediction have been hypothesis-based, where scientists select a certain feature that they believe changes prior to a seizure [5]-[8]. However, no feature has been found to be unique to the seizure onset, so these approaches have resulted in many false positives. The alternative approach we used is based on machine learning methodology where we supply an algorithm with enough data in which EEG is identified as preictal (immediately preceding a seizure) or interictal (ordinary between seizures), and let a computer optimize the algorithm to classify those two data sets[9]. This approach is powerful, for the combination of certain sets of features can be examined and complex relationships among the features for finding the seizure onset, which probably could not be found by a human, can be investigated.

Of the available classifiers we consider SVM, Neural Networks, and LDA for our classification process. In the previous research papers the output of three classifiers are taken separately and the output of the majority of the classifiers is considered as the final result. In this paper the innovation is that the weighted sum of all three classifiers is considered for the classification. The above classifiers are considered since the real-time implementation of the above classifiers is less complex and highly reliable with low false prediction rate (fpr).
II. METHODS

A. Outline and Data Acquisition

The seizure prediction algorithm consists of pre-processing, feature extraction, classification, and control mechanism, as outlined in Fig. 1. Each step will be discussed in its sub-section in detail.

To test the proposed epileptic seizure predictor, we considered the Freiburg EEG database, containing intracranial EEG recordings of 21 patients suffering from medically intractable focal epilepsy.

A detailed description and usage of this database can also be found in [10]. The amount of available data consists of at least 24 hours of interictal recordings for 21 patients with 2-6 seizures for patient and 50 min of preictal data.

B. Selection of Window

Window selection plays an important role; window size would differ from 0.5 seconds to 5 seconds. Selecting window would help in extracting useful information from EEG data without any loss. It was found that choosing 3 seconds window is optimistic. Sliding window method is employed, where window is moved on the EEG data to extract useful information.

C. Feature Extraction

It is the process where, useful information from the EEG waveform is extracted. There are numerous methods available to extract information from the available EEG waveform. Few are Linear Predictive coding taps, Fast Fourier transform, Auto-regressive models, Wavelet decomposition etc. The following are the features which we considered for system. Both univariate and bivariate features are extracted [11]-[18].

1. Power Spectral density: Different physiological and pathological processes are reflected by activity in different frequency ranges of the power spectrum \(P_f\) of the EEG. According to these ranges, a set of power spectral bands \((\alpha, \beta, \gamma, \delta)\) were defined in equations (1)-(4) in classical EEG analysis. The relative power contained in these bands can be defined as

\[
\theta_f = \frac{1}{P} \sum_{f_i=0.5Hz}^{13Hz} P_f
\]

\[
\alpha_f = \frac{1}{P} \sum_{f_i=8Hz}^{30Hz} P_f
\]

\[
\beta_f = \frac{1}{P} \sum_{f_i=13Hz}^{30Hz} P_f
\]

\[
\gamma_f = \frac{1}{P} \sum_{f_i=100Hz}^{300Hz} P_f
\]

where \(pf\) - spectral band power

\(P\) - total power

2. Energy: The accumulated energy is computed from EEG time series by integrating the broadband signal power (or energy) over a sequence of (possibly overlapping) windows in a moving window analysis. According to Parseval’s theorem, the average power of a signal is given by the variance, so the accumulated energy for the \(t\)-th time window is obtained by cumulatively summing the variance of all past time windows given by equation (5),

\[
E(t) = \sum_{k=1}^{t} (\sigma_k^2)
\]

Where \((\sigma_k)^2\) is the variance of the \(K\)-th window.

3. Autoregressive Model: The most general linear (univariate) model for a time series is the autoregressive moving average (ARMA) model. It is composed of three linear model processes: a purely random process (white noise), an autoregressive (AR) process and a moving average (MA) process. An AR process is defined by equation (6),

\[
x_t = \sum_{i=1}^{p} \alpha_i x_{t-i} + \epsilon_t
\]
and it indicates that the value of the time series at time point $i$ is a linear combination of its $p$ past values and a purely random process $\varepsilon_i$. In order to account for possible correlations in the noise, $\varepsilon_i$ may be modelled equivalently as an MA process given by equation (7),

$$\varepsilon_i = \sum_{l=1}^{q} b_l \varepsilon_{i-l}$$

indicating that the noise at time point $i$ is a linear combination of its $q$ past values. Hence an ARMA model is given by equation (8),

$$x_i = \sum_{l=1}^{p} a_l x_{i-l} + \sum_{k=1}^{q} b_k \varepsilon_{i-k}$$

where the coefficients $\{a_l\}$ and $\{b_k\}$ are to be determined by fitting the data, typically using a least-squares criterion.

4. Maximum cross correlation: In order to quantify the similarity of two signals $\{x_i\}$ and $\{y_i\}$ the maximum of a normalized cross-correlation function can be used as a measure for lag synchronization given by equation (9),

$$C_{\text{max}} = \max \left\{ \frac{C_{xy}(\tau)}{\sqrt{C_{xx}(0)C_{yy}(0)}} \right\}$$

$C_{xy}$ is the linear cross-correlation function.

D. Classification

Classification step helps in finding out whether the patient is in Preictal/ictal or interictal condition i.e. this is the main step which decides about prediction [19]-[21]. There are various classifiers which are broadly classified into linear and non-linear. Innovative idea in this paper is to have three classifiers LDA, KNN, SVM to increase reliability, reduce false prediction rate [22].

All three classifiers would classify the feature vector and decide the state of the patient. All three classifiers are not reliable in all the cases; however SVM classifiers are generally said to have high reliability. Here we use the weighted sum of the three classifiers for the classification process. Since SVM have high accuracy and are more reliable compared to other two classifiers, it is given with higher weights than the others.

E. Seizure Control By Vagus Nerve Stimulation

Vagus nerve Stimulation (VNS) is safe and reliable treatment adjunct for patients with medically intractable epilepsy [23]. VNS uses an implanted stimulator that sends electric impulses to the left vagus nerve in the neck via a lead wire implanted under the skin. Vagus nerve stimulation (VNS) is designed to prevent seizures by sending regular, mild pulses of electrical energy to the brain via the vagus nerve. These pulses are supplied by a device something like a pacemaker.
The battery life for the pulse generator is between 10 to 16 years, depending on the settings, i.e. how strong the signal being sent, the length of time the device stimulates the nerve each time, and how frequently the device stimulates the nerve. The device is currently only made by Cyberonics, Inc. The VNS device is sometimes referred to as a “pacemaker for the brain.” It is placed under the skin on the chest wall and a wire runs from it to the vagus nerve in the neck. The vagus nerve is part of the autonomic nervous system, which controls functions of the body that are not under voluntary control, such as the heart rate. The vagus nerve passes through the neck as it travels between the chest and abdomen and the lower part of the brain.

The neurologist programs the strength and timing of the impulses according to each patient’s individual needs. The settings can be programmed and changed without entering the body, just by using a programming wand connected to a laptop computer. For all patients, the device is programmed to go on for a certain period (for example, 7 seconds or 30 seconds) and then to go off for another period (for example, 14 seconds or 5 minutes). The device runs continuously, usually with 30 seconds of stimulation alternating with 5 minutes of no stimulation. The patient is usually not aware that it’s operating. Holding a special magnet near the implanted device causes the device to become active outside of the programmed interval. For people with warnings (auras) before their seizures, activating the stimulator with the magnet when the warning occurs may help to stop the seizure. Settings (also called stimulation parameters) set by the neurologist typically include a stimulation amplitude of 1.0 to 3.0 mA (milliamperes), a stimulation frequency of 30 Hz (hertz), and a pulse width of 500 microseconds. By adjusting these settings, the doctor not only may be able to control more of the patient’s seizures, but often can also relieve side effects.

### III. RESULTS

The performance of the classifiers is compared based on the false positive rates (FPR) of the classifiers. The false prediction rate of the proposed system is very low when compared with classifiers working individually. Table 1 gives the FPR values for proposed system and previous systems. The proposed system has very low FPR which tells that the system reliability is increased. If the system reliability increases the false trigger given to the VNS device decreases and hence side effects caused due to VNS device is decreased.

#### Table 1

<table>
<thead>
<tr>
<th>Patient’s Number from Database</th>
<th>SVM (FPR)</th>
<th>Neural Network (FPR)</th>
<th>Logistic Regression (FPR)</th>
<th>Proposed System (FPR)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>6.2</td>
<td>5.9</td>
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<td>2.7</td>
<td>1.8</td>
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<td>5.7</td>
<td>4.5</td>
</tr>
</tbody>
</table>

### IV. CONCLUSION

The proposed paper not only provides an effective and highly reliable system for the prediction of epileptic seizure but also a controlling mechanism using vagus nerve stimulation (VNS). The reliability of the proposed system increases because of the multiple classifiers used in the prediction system. Even if the vagus nerve stimulator does not
eliminate seizures, it might allow the doctor to reduce the amount of seizure medicines or lower the dosage. Compared to seizure medicines, the side effects of vagus nerve stimulation are dramatically different. Medicines for epilepsy can cause allergic rashes in up to 10% of people. They can damage the liver or blood cells, can interfere with other medication for different conditions, and can cause sleepiness, memory problems, and behaviour problems. They also may have long-term consequences like osteoporosis or damage to the nerves in the arms and legs. Vagus nerve stimulation has none of these effects. In fact, many patients feel more alert and interactive, which is very valuable for impaired patients, particularly children who are lethargic. The only common side effects of Vagus nerve stimulation are in the throat area, because a branch of the nerve goes to the vocal cords. When the device stimulates, the person may feel a tickle in the throat, a bit of a cough, or a softening of the voice but this is usually tolerable. Some other side effects, like pain or chronic hiccups, can be eliminated if the doctor adjusts the way the device is working.

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REFERENCES


