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Comparative Pattern Learning Framework for Seizure Prediction

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***Abstract*—** Epilepsy is neurological disorders affecting the quality of life by making people worry about future seizure events. Many of other seizure prediction research shows that some seizure prediction results are still need better and reliable prediction algorithm for helping to develop seizure prediction system. Electrocephalography (EEG) can be use for seizure analysis but using better algorithm we can create system that can give an alarm before seizure occur so patient or doctor can take appropriate action to overcome from the risk. In this study, few methods are compared to find better accuracy to find better algorithm. Using well mannered algorithm we can create automated seizure prediction system. Here, algorithms such as SVM (support vector machine), RA (Regression Analysis), and ANN (Artificial Neural Network) are compared. In this paper, we tried to compare the seizure prediction methods for getting more accurate results for the future work of predicting seizure type.

***Keywords*—** Support vector machine (SVM), artificial neural network (ANN), EEG, EPILAB Tool, Seizure prediction

I. INTRODUCTION

Seizure is neurological disorder that affects nearly 1 to 2% of the world's population [1] [3] [10]. The epilepsy occurs without warning, mostly in brain when excessive electrical discharge is limited to one of the part in it seizure occurs. During seizure, abnormal behaviour, symptoms (temporary confusion, a staring spell, uncontrollable jerking movements of arms and legs, Psychic symptoms such as fear, anxiety, etc.) and sensations, sometime includes loss of consciousness are common factors patient will face.

Depending upon the type of seizure, symptoms vary. Generally, patient with epilepsy will tend have same type of seizure every time, so the symptoms will be same. Neurologist doctors classify seizure as either generalized or focal, based on how activity of abnormal brain begins. The ability to predict the pattern of seizures could improve the treatment of patient and quality of life. It is observed that characteristics of EEG signals are different during abnormal and normal seizure events.

For identification of seizure there are many signal analysis techniques have been reported in past. [22] Basically brain is divided into two hemispheres: right and left hemisphere and it consists of four lobs: Frontal Lobe, Parietal Lobe, Occipital Lobe, and Temporal Lobe [1]. Each Lobe have symptoms, In the Frontal Lobe symptoms may include a Wave like sensation in the head; In the Temporal Lobe a feelings of having already experienced the present situations; In the Partial Lobe numbness or tingling; In the Occipital Lobe visual disturbance or daydream.

This report focus on data of abnormal and normal patients that further pattern can be achieved to help to predict next future seizure. Moreover, generalized seizure is different; appear to start in all parts of the brain simultaneously. Focal seizures are seizure which affects initially only one hemisphere of the brain (left or right).

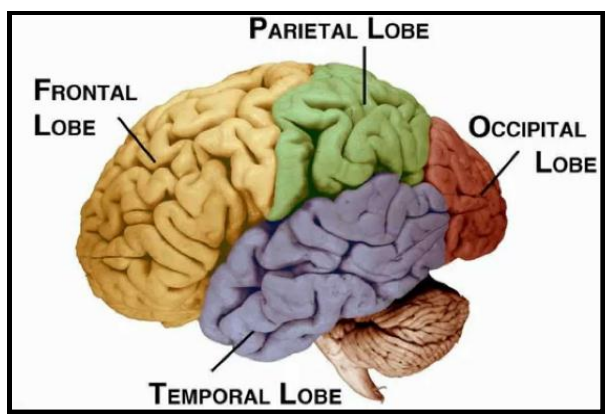

Fig: 1 Brain divided in terms of lobes [1]

Rest of the paper is organized as follows, Section I contains the introduction of seizure prediction, Section II contain the literature review, Section III contain a new study, and Section IV concludes research work with future research.

II. LITERATURE REVIEW

Saif Cao Xiao, Shouyi Wang, Leon Iasemidis, and Stephen Wong presented an adaptive pattern learning framework with approach of online feature extraction to get online seizure prediction. Moreover, a two-level online feature extraction approach is applied to analyze EEG (electroencephalogram) signals and develop pattern library by developing rules namely, adaptive probabilistic prediction, adaptive lineardiscriminant-analysis-based prediction(ALP), and adaptive naïve bayes based prediction(ANBP), gave accuracy around 79%, 78%, and 82% for APP, ALP, and ANBP, respectively.

Cao Xiao's approach gave a practical tool to solve the hardest seizure prediction problem. [1] Luigi Chisci and group have aimed prospective seizure prediction through pattern recognition methodologies [2]. The sensitivity of seizure was very high and appeared encouraging but it gives a wrong result of seizure prediction algorithm, which has to work not only for real time but online continuous electroencephalogram data which is shown by Freiburg team's latest publication [3] and also down result acquired about sensitivity through a fair specificity value when they sun their algorithm on long-term continuous EEG data. They use mean phase coherence and dynamic similarity index as well as logical "AND" and "OR" combination [3].

Most recent methods of seizure prediction are non-adaptive threshold-based approaches. But intra- and inter- individual variability of seizure makes difficult to develop a universal non-adaptive predictor. Threshold level for each individual patient is a not great idea. Therefore, there is need for an automated adaptive framework for epileptic seizure prediction. Leon D. Iasemidis and group [5] [6] developed optimization-based prediction algorithm which, based on dynamic synchronization in human epileptic brain over time. The adaptive seizure prediction algorithm (ASPA) was used and optimizing overall sensitivity (84%) [5]. P. Rajdev, M.P.Ward, and group [7] proposed an adaptive seizure prediction algorithm which was based on autoregressive (AR) model of EEG recording. There exists a rang of tools for analysis of EEG, including frequency domain methods [8],[9] and more complex representation like wavelets [10],[11], Markov processes [12], or particular synchronization index [13].

All electroencephalogram features are calculated over a short time window of a few second so r minutes. There are two kind of measures; univariate measures, computed on each EEG channel separately, and vicariate (or multivariate) measures, which quantify few relationship, between two or more EEG channel. A huge amount of features of univariate have been investigated for seizure prediction [4], [14], but none of them have obtained high performances, moreover, according to an extensive study comparing most univariate and vicariate techniques[15],they confirmed the superiority of vicariate measurements for seizure prediction.

III. A NEW STUDY

A new study is based on Raw EEG data or also can be on previously calculated features [9]. Here, let's start with raw data, this support different binary format, including Mat-files, TRC files, and Nicolet files. Raw data in a several files or particular files can be gained [9]. In case of multi-files, EPILAB is able to assess directories of files, and create an internal mapping such that all the data can be managed as if they were in a particular file [9].According to the study of formation, the information needed for future processing is achieved such as frequencies, event occurring during the recording (seizure time), sampling, temporal gaps between files and electrode description [8].

Once a study is created, EEG signals can be shown using the raw data navigation tool integrated in EPILAB [9]. We can visualize a data window with a specified time-length with two main modes of navigation are by time and by EEG annotation events [9]. According to it seizure onsets and offsets marked can be easily locates and also filtered visualized data. A study using previously computed features, user can integrate more than one file. This may computed using same computation parameters [8]. EEG raw data that have been indicates to be helpful in seizure prediction [8].

3.1 Feature Extraction

There are several measures either based on Univariate (one channel) or on Multivariate (multiple channel), and are computed in a window-by-window basis. The infinite impulse response forward-backward Butterworth filters can be used: low-pass, notch, and high-pass, that minimize power line interfaces [8]. Butterworth filter creating a uniform acceptance of the needed EEG frequencies. And the other filters they provide a large transition band, which can be minimized by expanding the order of filters [8].

3.1.1 Univariate EEG features

The "decorrelation time" is the time of first zero crossing of the autocorrelation sequence of a given EEG signal. If the decorrelation time is down, than less correlated the signal is [9]. Hjorth's parameters of mobility and complexity quantify the root-mean-square frequency and expand the root-mean-square frequency of a given signal. Non-linear univariate measures are often depends on the rebuilt of the state space trajectory from a given univariate time series. In different frequency bands the spectral power of the EEG was also considered for seizure prediction. The "spectral edge frequency" is an expression of a power distribution along the spectral range of a given signal.

EPILAB also includes statistical moments: mean variance, skewness, and kurtosis. The energy of the signal is equivalent to variance; skewness is a measure of the symmetry of the amplitude distribution and kurtosis is a measurement of the relative peakness or flatness of the amplitude distribution [14]. It was announced that variance and kurtosis were vary significantly in the preictal state. Wavelet transform enables a time-frequency decay of a presented signal in several sub-bands. This enables measurement of the energy in different frequency ranges [15].

3.1.2 Multivariate EEG features

EEGLAB support the removal of linear and nonlinear multivariate compute. These features are obtained from the combination of two or more channels. LC (Linear coherence) is a compute for the contact depends on the auto-spectrum and cross-spectrum between two time series at a present frequency. MI (Mutual information) is a non-linear measure for inter-dependence depends on entropy and joint-entropy of two time series [14] [15]. The DTF (directed transfer function) and the PDC (partial directed coherence) are methods quantifying the direction of inter-actions. They model the EEG signals by a VAR (vector autoregressive model). So far, directed transfer function and partial directed coherence have been mainly appeal to learn the interaction between neural structures and for the localization of the epileptic focus and seizure propagation [15].

Table-1 Data Features based on Univariate & multivariate [8]

		Features
1.	Univariate	AR modelling predictive error
		De-correlation time
		Energy
		Hjorth
		Non-linear
		Relative power
		Spectral edge
		Statistics
		Energy of the wavelet co-efficient
2.	Multivariate	Coherence
		Correlation on the probability of Recurrence
		Directed transfer function
		Mean phase coherence
		Mutual information
		Partial directed coherence

MPC (Mean phase coherence) is a statistical measure for phase synchronization between two time series. Variations in MPC were announced and even hours before the seizure onset. The CPR (correlation on the probability of recurrence) is a measure of detect inter-action between two time series based on recurrence probabilities of recurrence plot. It was reported that figure could be applied to noisy time series and non-phase-coherent [15].

3.2 Computation Times

Table 2 shows the time to calculate a group of features for data. The information is provided as the digit of times that a group of features is highest to calculate similar to the window duration [8]. A number lower than one means that the similar group of features takes more time to calculate than the window duration. Otherwise, it means that a group of features can be calculated in a part of time lower than the window duration [8].

The raw data was acquired at 1024 Hz. One channel was considered for univariate case. Data from two channels was analyzed in the multivariate case [8]. All the univariate EEG features alone can be obtained multiple times faster than real-time for one channel for a modern personal computer. And for univariate features real-time analysis of more than 100 channels is feasible [9].

3.3 Feature Computation Setup

For feature extraction the first step is the choice of electrodes that should be analyzed [13]. After choice of electrode the user can describe the window size and the step size used for a sliding window measure. If the step size is smaller than the window size than the window may overlap [13]. Gaps are automatically detected within the recording. For every window, a feature sample is obtained for every channel in the univariate phase or for each possible pairs among the different channels in the multivariate phase. The feature samples can be retaining a binary file [13]. Features saved in binary files can be used to develop studies based directly on features [13].

Table-2 Features that are possible to extract from raw data and related computation time information [8]

		Features	Comp. Time (* fast. Win Dur)
1	Univariate	AR model in predictive error	1000.0
		De-correlation time	1162.8
		Energy	6250.0
		Hjorth	357.1
		Non-linear	5.0
		Relative power	384.6
		Spectral edge	609.8
		Statistics	943.4
		Energy of the wavelet co-efficient	192.3
2	Multivariate	Coherence	9.4

		Correlation on the probability of recurrence	0.8
		Directed transfer function	2.4
		Mean phase coherence	56.8
		Mutual information	0.5

3.4 Seizure Prediction

There are two kind of prediction format, which are integrated into EPILAB. These can be depending on classification algorithm or threshold.

3.4.1 Threshold based analysis

For each feature a threshold is calculated such that the alarms triggered at threshold crossing yield optimal predictive performances in threshold based analysis. [13].This approach can be expanded by the probability to pair up two or more feature by using logical “AND” and “OR” operations. Additionally, independent threshold can be observed for day and night, such that circadian rhythms can be judged [13]. In order to measure the performance of given seizure prediction method, the seizure prediction characteristics was suggested, which is depend on clinical and statistical reflection. The seizure prediction characteristic allows an evaluation of quasi prospective prediction performance by observing the alarms triggered. Here, an alarm is considered right if it is triggered at a given time before seizure onset [13].

In order to measure the time during which the seizure has to be prospect, the seizure occurrence period (SOP) was explain. Aiming to allow an intervention to be applied, the alarm has to introduce the SOP by a exact time, the intervention time (IT) [13].Similarly, the minimum IT and maximum SOP should be explain. If an alarm following a first alarm throughout a short time period would be observed to prolong the first alarm this could guide to extra long prediction windows.

Hence, these interludes do not enter in the determining of the false prediction rate (FPP) [13]. The seizure prediction characteristics also add an approach for the statistical validation of prediction performances [13]. Based on an analytical random predictor, critical performances values can be calculated which could be reached by prospect. Furthermore, it gives valid result for few numbers of seizures, which are somehow similar in seizure prediction studies [13].

3.4.2 Classification

EIPLAB qualify the application of two kinds of classifiers: Artificial neural networks (ANN), Support vector machines (SVM).

3.4.2.1 Artificial neural networks

Artificial Neural Networks (ANN) are adaptive, non-linear structures that execute a distributed computation of a stated set of input signals [13] [7]. Through a set of processing element the distributed processing is managed, called neurons, and organized in one or many processing stages [13]. Each neuron collects connection from other neurons, from its own output or from the network inputs. The ANN is a feed forward network when no internal feedback is remembered, otherwise a recurrent one [13]. At each neuron, the signals are multiplied with adjustable parameters called weights [13]. The output of a stated neuron is the sum of the entire weighted relation modified by a function, called activation function.

The supervised training of an ANN is the evaluation of the weights in a repeating way, trying to inexact the network output as most as possible to a predefined optimal output, called target [13]. The mean squared error means the degree of approximation is set by an error function [13]. EPILAB enables the concern of feed forward and recurrent networks instruct by a various of algorithms, align from the standard error back propagation (BP) to more robust strategies [13].

3.4.2.2 Support vector machine

The structure of Support Vector Machine (SVM) is similar to an Artificial Neural Networks (ANN); is very different the way it is constructed. The plan behind Support Vector Machine is that data can be changed into a higher-dimensional space in which elements situated to two different classes can be linearly divided [15]. The he high-dimensional space should be substantially larger than the input space dimension, qualify the definition of hyper plane with the largest margin separating the two classes [15].

It is capable to resolve a two-class problem. However, there is case where more than two classes are required to resolve a sated classification problem [15]. For this purpose Support Vector Machine (SVM) were also adjusted to execute classification in more than two classes. The standard approach is to diminish a multi-class problem to various two-class problems, for which the standard support vector machine algorithm can be applied.

3.5 Classification Procedure

The first step for the occurrence of a seizure prediction based on classification methods includes the final answer about the inputs of the classifier and about the temporal division of the data into training and testing sets. EPILAB allow straining on one part of the training dataset and prospective counted in a second part of the testing data. The training data must have data of all the cerebral phase; it should integrate digits of seizure and interictal data, allow in gap roper optimization of the classifier. Also, the out-of-sample data should be long sufficient and at least one seizure, permitted presentation rating.

More to the input time series, at target output is necessary for the training of the classifier. The final output is a time series that distinguish the cerebral state for every input. EPILAB consider stwoor four cerebral states, resulting in a classification in two or four classes.

The four-class point of view observed that the input can be classified as: Interictal- the "normal" brain state,
Preictal- the previous time to the seizure onset,
Ictal- the interval time during seizure,
Postictal- the time between a seizure and a "normal" brain state

IV. CONCLUSION

Till now, Support Vector Machine, regression model, artificial Neural Network, adaptive probabilistic prediction, adaptive lineardiscriminant-analysis-based prediction, and adaptive naïve bayes based prediction, Genetic algorithm and so on used for seizure prediction. From all algorithms comparative study of different methods for seizure prediction and classification, Support Vector Machine (SVM) method is most suitable and accurate. Methods for the detection or prediction of other kind of events can be executed if the final, threshold values, and performance evaluation functions are adjusted accordingly. Using Support vector machine (SVM) and Artificial Neural Network (ANN) classification is done with accuracy 87% and 68%, respectively. This comparison can be useful for future seizure prediction analysis system so that patient can get alarm before upcoming seizure. So to obtain higher classification accuracy various algorithm can be used and to detect accuracy SVM, ANN, RN can be used.

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