Original Article

An Efficient EEG Channels-Selection Approaches For Epilepsy Seizure Prediction

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Abstract

In this study, we are interested in the epilepsy seizures problem. Indeed, we used binary SVM to predict the ongoing seizures and multiclass SVM to predict different states of patients' epilepsy. Brain activity is used as an efficient source for predicting seizures, it's recorded in Electroencephalography (EEG) segments signal. We propose and compare in this paper, three ideas select channels: the highest frequency channels, the channels of the left part of the head, and the channels of the right part of the head. A features extraction stage is important to produce a rich and relevant dataset, in effect, 22 features are calculated for each segment of 5 min from EEG signal. A binary SVM is used to predict the ongoing seizures named pre-ictal, and a one-versus-all multi-class SVM is used to predict four classes (pre-ictal, ictal, inter-ictal, and post-ictal). A classification rate toward 97%, on the selected channels corpus, was achieved by SVM (binary and multiclass) with the majority of patients.

Keywords—Epilepsy Seizure, EEG, channels, prediction, SVM.

I. Introduction

Epilepsy is a frequent neurological state that has an impact on the central nervous system and caused seizure phenomena. Epilepsy seizure is a common neurological trouble, and it affects an important percentage of people in different countries. This unnatural state of the nervous system produces disruptions of neural activities, which are shown in emotions, muscle convulsions, and loss of consciousness.

The most invention for understanding epilepsy is that of Hans Berger in 1924. Indeed, the latter set up a device called an electroencephalograph (EEG) which makes it possible to collect and save the electrical activity in the head. The EEG is a multi-channel tool used to record the electrical activity produced by a number of neurons in the brain using multiple channels placed in different positions of the brain. In practice, EEG has been a fundamental tool, especially in the identification of epilepsy.

Automatic detection of the EEG signal is a basic tool that facilitates the identification of epilepsy and improves the exploitation of EEG signals. Since 1970 important attention has been paid to automatic seizure detection. However, feature extraction is an important stage to read the hidden information from EEG signals and describe the behavior of EEG signals. The feature extraction step should decrease the original signal to a smaller dimension as possible and contain the maximum amount of relevant information.

In general, the EEG signal is pre-processed and after it's passed to a recognition system based on machine learning methods like neural networks, and support vector machines. Many systems have been proposed with the goal of improving the automatic detection and prediction of crises from EEG signals. Several types of feature extraction from epileptic EEG data have been proposed, such as parametric and non-parametric methods, time-frequency methods. The feature extracted are used for distinguishing between classes of epileptic. Some works will good be discussed in the related works section.

The rest of this paper is organized in this way. In section 2, we talk about some related works. In the following section, we present briefly the support vector machine algorithm. In section 4 we introduce epilepsy seizure prediction and EEG signals. In section 5, we present the implementation and results. Finally, the last section is reserved for the conclusion and some observations relating to future works.

II. RELATED WORKS

EEG classification is most used in the detection and prediction of epilepsy seizures. Usually, a pre-processing stage is necessary to extract appropriate features from the EEG signal, in order to predict seizures. Many works are proposed for automatic prediction such as Alexandros and all in [1] used the time-frequency analysis approach to predict epileptic seizures from EEG signals.

Authors in [2] apply the discrete wavelet transform to generate sub-bands of EEG signals, in order to detect the ongoing seizure. In [3] Authors present a new method of seizure detection, using a multi-channel long-term. Indeed, the authors use fractal geometry to extract fractal intercept as a nonlinear feature of EEG signals, and they calculate a linear feature named relative fluctuation index. All extracted features are given to neural network models for classification tasks.

The authors in [4] apply the time-frequency domain to analyse the EEG signals. Initially, the authors split the EEG signal of a set of windows using time-frequency. After that, several features are extracted for each window. these features are concatenated and given to an artificial neural network architecture classifier. Authors in [5] propose a Bag-of-Words model to extract features from EEG signals, in the pre-processing step. Moreover, they use classifiers based on kernel methods to detect epilepsy seizures.

In [6], the authors present an architecture neural founded on deep learning for detecting seizures, in the case of paediatric patients. The data used represent EEG signals recorded by several channels placed on the head. The proposed approach consists of two parts: ahead, an autoencoder with two dimensions is created and connected to a supervised neural network classifier, with two classes the ictal state and interictal state.

In [7] authors propose a new neural network architecture to detect seizures in patients with partial epilepsy. They use neuronal potential similarity tools to create their system of detection.

In [8] a review is proposed, the authors in this paper give a survey about recent research in epilepsy seizure, time- or frequency-domain for signal pre-processing, and machine learning methods used to classify seizure states.

III. SUPPORT VECTOR MACHINES

Support Vector Machines (SVM) is a famous algorithm in the machine learning universe, SVM is classed as a kernel method with a background in statistical learning [9,10,11]. SVM machines have been successfully used in several domains with different tasks such as classification, regression, prediction, and clustering [12,14]. Originally SVM is a binary classifier, in their general principle, SVM finds the best or the optimal linear hyperplane or separation surface, in terms of a higher bound on the risk that can be explained as the geometrical margin, to a real risk using special functions named kernels k(x,y). Usually, kernel functions make sense of a similarity measure of each pair of examples from the training dataset X. In their classical formulation, SVM is given as an optimal hypothesis calculated through a sum of the following equation (1).

$$f(x) = \sum \alpha_i\, k(x, x_i) \qquad (1)$$

Where α_i are the elements of the unique solution of a quadratic programming (QP) problem with linear equations, the size of this QP is related to the number of examples used in the training stage. The solution of QP obtained is mostly very distributed, and the not null represents the critical points or called also support vectors (SV's). Clearly, the number of these critical points defines the response time which is the time it takes to classifier arrival examples or observations. Furthermore, the response time is very important, especially in real-time applications such as the prediction of seizures, speech recognition, etc.

On the other hand, one of the benefits of the kernel method in particular SVM is the possibility to use data with different dimensions. That propriety doesn't exist in other methods such as neural network architectures, this advantage is assured by kernel functions.

During the training step, all input data (training dataset) are projected in a new linear space, as the inner product of the images of each pair of examples x and y, using a kernel function k(x,y).

Moreover, the optimal hyperplane can be computed with the kernel previously determined for data with different dimensions. The formulas (2, 3, 4, 5) give the most used kernels for a variety of applications.

linear

$$k(x, y) = x^T y \qquad (2)$$

polynomial

$$k(x, y) = (\gamma x^T y + r)^d, \gamma > 0 \quad (3)$$

Gaussian

$$k(x, y) = \exp(-\gamma \|x - y\|^2), \gamma > 0 \quad (4)$$

Laplacian

$$k(x, y) = \exp(-\gamma \sum |x, y|), \gamma > 0 \quad (5)$$

A. SVM Formulation and training

Given a set of examples $x_i \in \Re^n i = 1, \ldots\ldots, m$, represent two classes, and a vector $y \in \Re^m$ such that $y_i \in \{1, -1\}$. The support vector machine (SVM) [10,11,12] solve the Lagrangian dual problem, with two linear constraints, as given by the formula (6).

$$\begin{aligned} &\text{maximize} \quad W(\alpha) = \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j y_i y_j k(x_i, x_j) - \sum_{i=1}^{m} \alpha_i \\ &\text{under the constraints :} \quad \forall i,\ 0 \leq \alpha_i \leq C \quad (6) \\ &\qquad \sum_{i=1}^{m} \alpha_i y_i = 0 \end{aligned}$$

The following function represents the optimal separation surface:

$$f(x) = \sum_{i=1}^{m} \alpha_i\, y_i k(x, x_i) + b \quad (7)$$

Where b is the bias term, this term is calculated in a different way as mentioned in [14]. Evidently, the final decision function (hyperplane) f depends only on the critical points or the coefficients α_i. To optimize the QP objective function, a similarities matrix is generated by the kernel $k(x_i, x_j)$ between the training examples x_i andx_j, this matrix is named Gram matrix K.

The dimension of the QP and consequently the dimension of the gram matrix depends just on the number of training sets d. This property makes the SVM classifier very soft for data of high dimensions. However, if the number d has an important value, SVM will face complex problems such as temporal and spatial complexities.

B. Multiclass extensions

As mentioned in section III, SVM is a binary classifier i.e. it's created for separating between two classes: positive and negative. But in general cases, we will have problems with more than 2 classes, which requires finding extensive approaches adequate to multiclass problems. A number of works have been proposed in the literature to extend binary SVM machines to multiclass cases, such as works in [18, 21].

Typically, Usually, multiclass SVM classifiers are constructed by combining a set of binary SVM machines. The popular multiclass approach is the one-against-all [10,13,15] that builds K classifiers, where K is the number of categories. The k^{th} classifier is constructed as follows: all examples of the k^{th} class will be labeled as a positive class and the rest of the examples, of all other classes, will be labeled as a negative class. The final function is given by the next expression:

$$f_{\text{One vs All}}(x) = \operatorname{argmax}_{i=1,\ldots\ldots,k}(f_i(x)) \quad (8)$$

An alternative common method is proposed for multiclass SVM, it's based on the training of each pair of classes separately, with the aim to build $\frac{k(k-1)}{2}$ binary SVM classifiers matching all the couples of classes possible. this approach is called one-versus-one (OVO). In the final step, we chose the class most representative by voting trick or building a directed acyclic graph where each node is a binary SVM classifier (DAGSVM) [16].

IV. PREDICTION OF EPILEPTIC SEIZURE

The goal behind the development of prediction systems is to identify ongoing seizures and help clinicians to understand phenomenon seizures. Automatic seizure prediction machines are created to: detect the existence or not of epilepsy seizures, and predict the coming epilepsy seizures, before there are happening. A variety of artificial intelligence algorithms are used to predict epilepsy seizures, from different biometric signals. All these algorithms involve two main steps:

- First, features extraction from biometric signals, such as electroencephalograph signals.

- Second, a classifier model is created to detect or predict seizures, this model is derived from machine learning methods, trained on sets of features called training data, and validated on testing data. In this stage, the machine learning tool used will discover and acquire all indicators about seizures.

In this paper, the features are computed from EEG signals, and the classifier model is constructed by the support vector machine method. In this study, we are interested in the epilepsy seizures problem. Indeed, we used binary SVM to predict the ongoing seizures i.e predict pre-ictal (the period before time seizure state) stat, and multiclass SVM to predict all states of epilepsy patients i.e classification of four classes: pre-ictal (the period before time seizure), ictal (time of seizure), inter-ictal (the period between two seizures), and post-ictal (After epilepsy seizure state).

A. EEG signal

Acquisition An electroencephalogram (EEG) is a tool used to acquire the electrical activities of the brain, using channels placed on the head. EEG provides a source rich in pieces of information concerning different activities, such as epilepsy seizures. Analyse of EEG is indispensable for the prediction and classification of epilepsy seizures because it furnishes information in real-time and with an excellent temporal resolution. EEG is one of the main diagnostic tests for epilepsy. While EEG provides an important set of data that can be analysed and interpreted via several methods. But it's very hard for patients to use the EEG channels for a long time.

In this study, we are using 22 features extracted from EEG signals windows, captured by channels placed in the scalp of the head. In this work, two parameters are used in features extraction step: the window size is fixed at 5 min and two values of 30 min and 10 min are chosen for the prevision time or pre-ictal time. furthermore, in this work we used 22 different features defined in EPILAB project of Center for Informatics and Systems for Informatics and Systems, Department of Informatics Engineering, University of Coimbra, Portugal [19].

B. Channels selection from EEG signal

In this study, we are interested in epilepsy seizure prediction from EEG signals. The channels or channels selection step is an important operation to extract the best features. We are used based in this work on three selection approaches:

- The highest frequency channels i.e. we select the channels that are the highest frequency for the 8 patients, as shown the table I.
- The left frequency channels i.e. we select the channels that are positioned in the left part of the head for the 8 patients, as shown the table II.
- The right frequency channels i.e. we select the channels that are positioned in the right part of the head for the 8 patients, as shown the table III.

TABLE I HIGHEST FREQUENCY CHANNELS SELECTED

Patient	**Highest frequency channels**
P 1200	AF7, F7, T7, P7, F9, T9, FT7, FT9, TP7
P 1500	FP2, F8, T8, P8, AF8, F10, T10, FT8
P 2100	FP1, AF7, F7, F3, F8, AF8, F9, F10, T9, T10, FT9, FT10
P 2300	F7, F3, T7, C3, P7, P3, F9, T9, FT7

TABLE III LEFT POSITION CHANNELS SELECTED

Patient	**Left channels**
P 1200	FP1, AF7, F7, T7, P7, F9, T9, FT7, FT9, TP7
P 1500	FP1, AF7, F7, T7, P7, O1, F9, T9, FT7
P 2100	FP1, AF7, F7, F3, T7, C3, P7, F9, T9, FT7, FT9, TP7
P 2300	AF7, F7, F3, T7, C3, P7, P3, O1, F9, T9, FT7

TABLE IIIII TABLE 3. RIGHT POSITION CHANNELS SELECTED

Patient	Right channels
P 1200	FP2, F8, T8, P8, AF8, O2, F10, T10, FT8, FT10, TP8
P 1500	FP2, F4, F8, C4, T8, P4, P8, AF8, F10, T10, FT8
P 2100	FP2, F4, F8, AF8, F10, T10, FT8, FT10.
P 2300	F8, FT8

V. IMPLEMENTATION AND RESULTS

In our experiments, we are used 4 patients from the EEG dataset of Coimbra university [19]. The features extracted from EEG data, with three methods of channels selection, are used to construct:

- A binary SVM classifier for seizures detection i.e pre-ictal class versus the rest of classes {ictal, inter-ictal, post-ictal}.
- A multiclass SVM classifier for seizures prediction i.e classification with four classes {pre-ictal, ictal, inter-ictal, post-ictal}.

In this work, all experiments were executed on the processor Intel i3 CPU 3.40 with 4 Go memory, and the Windows 7 operating system. Moreover, a 3-fold cross-validation algorithm is used to optimize the SVM parameters g and C. The GNU LibSVM [17] software was used as an SVM implementation. All experiments are realized with parameter C=100 and Gaussian kernel parameter g=0.3. The training data is constituted of 67% of all data or features extracted from EEG, and the test data is constituted of 33% of all data.

For the evaluation, three criteria are used: precision, recall, and accuracy. The precision and recall are very used to evaluate binary classification, it's given by the two next formulas:

$Precision = TP / (TP + FP)$ (9)

$Recall = TP / (TP + FN)$ (10)

The accuracy is a general measure used to evaluate any classifier, it's is given by:

$Accuracy = (TP + TN) / M$ (11)

Where: TP is true positives, TN is true negatives, FP is false positives, FN is false negatives, M is the total number of testing examples.

A. Discussion

The following tables summarize the obtained results (in percent), for each patient with different methods of electrode selection. Table IV gives prediction results for ongoing seizures with 10 and 30 min before (pre-ictal) obtained by the SVM binary classifier, and for features calculated from the highest frequency channels.

Tables V and VI present predictions of ongoing seizures with 10 and 30 min before seizure obtained by SVM binary classifier for all left and right channels respectively.

It's clear that the accuracy is different for each patient, and while we are close to the seizure instance, as shown in figure (Fig. 1). For binary classification, the precision and the accuracy give a good image of the ability of the classifier. In general, SVM gives encouraging results for prediction of the ongoing seizures, versus some works cited in [20]. On the other hand, the results obtained by the three approaches, used in the select channels, are similar with a simple advantage for the highest frequency channels approach.

TABLE IVV BEST PREDICTION RESULTS OF ONGOING SEIZURE WITH HIGHEST FREQUENCY CHANNELS

Patient	Pre-ictal	Accuracy	Precision	Recall
P 1200	30	78.44	78.44	100
	10	91.81	91.81	100
P 1500	30	88.25	88.25	100
	10	96.08	96.08	100

P 2100	30	97.72	97.72	100
	10	98.89	98.89	100
P 2300	30	95.81	95.81	100
	10	98.60	98.60	100

TABLE V BEST PREDICTION RESULTS OF ONGOING SEIZURE WITH LEFT CHANNELS

Patient	**pre-ictal**	**Accuracy**	**Precision**	**Recall**
P 1200	30	78.44	78.44	100
	10	91.81	91.81	100
P 1500	30	88.25	88.25	100
	10	96.08	96.08	100
P 2100	30	97.72	97.72	100
	10	98.89	98.89	100
P 2300	30	95.81	95.81	100
	10	98.60	98.60	100

TABLE VI BEST PREDICTION RESULTS OF ONGOING SEIZURE WITH RIGHT CHANNELS

Patient	**pre-ictal**	**Accuracy**	**Precision**	**Recall**
P 1200	30	78.44	78.44	100
	10	91.81	91.81	100
P 1500	30	88.25	88.25	100
	10	96.08	96.08	100
P 2100	30	97.72	97.72	100
	10	98.89	98.89	100
P 2300	30	95.81	95.81	100
	10	98.60	98.60	100

However, table VII illustrates the prediction results of all states of the patient i.e the multiclass case of highest frequency channels with SVM multiclass. We note that the left and right channels give the same results.

TABLE VII BEST PREDICTION RESULTS OF THE FOUR STATES OF PATIENT WITH HIGHEST FREQUENCY CHANNELS

Patient	**pre-ictal**	**Accuracy**
P 1200	30	60.34
	10	73.01
P 1500	30	80.13
	10	87.74
P 2100	30	96.08
	10	97.05
P 2300	30	93.97
	10	96.30

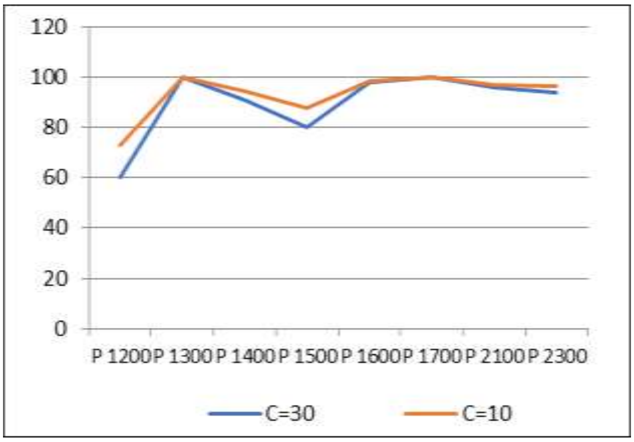

Fig. 1 Variation of accuracy prediction for 30 min and 10 min pre-ictal duration with highest frequency channels.

VI. CONCLUSION

In this paper, we have presented and discussed a competitive approach for channels selection to extract the best features, with the aim to create prediction models for Epilepsy seizures using a support vector machine. We are concluded that they aren't a difference between the left and the right positions of the channels. Indeed, the selection of the channels whose highest frequency is sufficient.

On the other hand, SVM gives encouraging results. It gives better accuracy for each patient, especially, for binary classification or the prediction of the ongoing seizures. However, as can be seen from the results, we created a prediction model for each patient, which indicates that we are at the beginning of this search axes.

Finally, it's necessary to invest in research on automatic epilepsy seizure prediction tools, with the goal to develop efficient predictors able to handle several patients in a common model.

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