Seizure detection using common spatial patterns and classification techniques

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***Abstract*—This paper investigates the effectiveness of Common Spatial Patterns (CSP) analysis of EEG signals on the automatic detection of focal epileptic seizures. Focal seizures are characterized by unilaterally triggered abnormal brain activity. CSP analysis has been frequently used in literature for multichannel EEG signal separation between two states. In the present study, EEG recordings from 10 subjects aged 7.7±4.4 years, including 63 seizures, were analyzed with respect to seizure detection and discrimination between interictal and ictal periods. Machine learning techniques of feature selection and classification were used in the analysis, resulting in a best achieved classification accuracy of 91.1%.**

Keywords—common spatial patterns, EEG, seizure detection, focal epilepsy, CSP

I. Introduction

Epilepsy is a neurological disorder characterized by an enduring predisposition to generate epileptic seizures [1] with great neurological, cognitive, psychological and social consequences. According to the World Health Organization (WHO), it is estimated that in 2019, epilepsy affects around 50 million people worldwide which is quite common in childhood [2].

In this study, focal seizures were investigated from pediatric patients. The definition and the classification of seizures originally based on the 1981 ILAE classification [3] which was recently revised by the ILAE to meet advances in scientific knowledge [4]. A fundamental distinction is made between focal seizure onset (seizures that arise in one hemisphere of the brain); generalized (originate in both hemispheres simultaneously); and seizures of unknown onset. Focal seizures are further subclassified depending on whether awareness (a marker for consciousness) is intact or impaired. Next, focal seizures are divided into motor or nonmotor. A seizure that begins focally (in one part of the body) and then spreads bilaterally is termed focal to bilateral tonic-clonic. Tonic refers to stiffening, and clonic to rhythmical jerking.

In order to diagnose and determine the cause of seizures, an expert neurologist evaluates clinical image, medical history, symptoms and various diagnostic methods. These methods include neurological exams, blood tests, EEG, ECG, MRI, fMRI, PET, CT, etc. Electroencephalography (EEG) remains the most widely adopted clinical technique for seizure diagnosis, detection, and anticipation. Detecting and locating the seizure period in EEG recordings manually, especially during long-term monitoring, may be time-consuming and tedious limiting the effectiveness of the treatment.

Various methods have been developed based on EEG signal and/or other biosignals analysis supporting automatic seizure detection [5-8]. Advanced signal processing techniques enable the signal decomposition on their temporal and spectral components. Common Spatial Pattern (CSP) is a feature extraction algorithm used in different applications, such as EEG signal analysis for motor imagery purposes [9, 10], and seizure detection [11-13]. It provides a method to extract features from multivariate signals that best represent the underlying brain activity for a specific task. A challenging issue is to use spatial filters in order to extract robust, representative features for seizure discrimination.

In this study, we use CSP algorithm-based features of EEG spectrum and its subband rhythms for automatic seizure detection. Then, we apply feature ranking and classification methods for discriminating interictal and ictal periods.

II. Methods

A. Common Spatial Patterns

The Common Spatial Pattern (CSP) is a signal processing method [9], mainly used in EEG analysis. Specifically, it has been used in the area of brain-computer interface (BCI) in order to extract signals' features that best represent the underlying brain activity for a specific task, such as hand/foot movement or to separate EEG patterns in epilepsy [12].

The CSP method aims to categorize multivariate timeseries data into selected categories. It pursuits to estimate a set of spatial filters that maximize the filtered signals' variance of one's category and at the same time minimize the filtered signals' variance of the other category [14]. Initially, the covariance matrix S of multivariate data E (MxN, N: samples, M: channels) is calculated as

$$S = \frac{E \cdot E^T}{trace\{E \cdot E^T\}}$$

where trace is the sum of the diagonal elements. The S is calculated for each signal segment and then we calculate the average spatial covariance matrix for each class separately

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DOI 10.1109/BIBE.2019.00166

$$\overline{S_c} = \frac{1}{K}\sum_{k=1}^{K} S_{(c,k)}$$

where c represents the class, k is the trial and K is the total number of trials for the class c. The corresponding eigenvectors and eigenvalues of the $\overline{S}_1 + \overline{S}_2 = \hat{U} \times \hat{\Lambda} \times \hat{U}^T$, where $\hat{U}$ is the eigenvectors matrix and $\hat{\Lambda}$ the diagonal matrix of corresponding eigenvectors are estimated. For the construction of the final projection matrix, several matrices need to be calculated. Initially, we calculate $\hat{P} = \hat{\Lambda}^{-1/2} \times \hat{U}^T$, then the average spatial covariance matrices $\tilde{\Sigma}_1 = \hat{P} \times \overline{S}_1 \times \hat{P}^T$ and $\tilde{\Sigma}_2 = \hat{P} \times \overline{S}_2 \times \hat{P}^T$. Furthermore, $\tilde{\Sigma}_1 = \hat{B} \times \hat{\Lambda}_1 \times \hat{B}^T$ where $\hat{B}$ is the eigenvectors matrix and $\hat{\Lambda}_1$ the diagonal matrix of the $\tilde{\Sigma}_1$. The final projection matrix is defined as $\hat{W}_0 = \hat{B}^T \times \hat{P}$. The first and last columns of $\hat{W}_0$ are the most important spatial patterns that explain the largest variance of one task and the smallest variance of the other.

For each patient, the 50% of data are used to train the model for the 2 classes (interictal, ictal). Then, a 19x19 channel matrix (projection matrix) is calculated which is used to extract the final 19 CSP features for each time window segment. Specifically, a segment E is first projected as $\hat{Z} = \hat{W}_0 \times \hat{E}$. Then, a 19-dimensional feature vector **y** is formed from the variance of the rows of $\hat{Z}$ as

$$\hat{y}_n = \log\left(\frac{\operatorname{var}(\hat{Z}_n)}{\sum_{n=1}^{N} \operatorname{var}(\hat{Z}_n)}\right)$$

where $\hat{y}_n$ is the n-th component of $\hat{y}$, $\hat{Z}_n$ is the n-th row of $\hat{Z}$, $\operatorname{var}(\hat{Z}_n)$ and is the variance of the vector $\hat{Z}_n$. The EEG is divided into spectral rhythms δ (0.5-4 Hz), θ (4-8 Hz), α (8-13 Hz), β (13-30 Hz) and total spectrum. We estimated the CSP features for each of these 5 different spectral bands. The spectral content of each rhythm enriches the information provided in order to improve discrimination ability.

B. *Machine learning techniques*

Machine learning techniques (automatic feature selection and feature classification) have been widely used in many research areas, serving classification problems such EEG analysis, emotional states recognition, BCI, motor imagery and epileptic seizure detection [15-17]. In this study, the idea of automatic seizure detection is underpinned by the process of training a classification model to effectively discriminate between interictal and ictal signals, along with the preceding processes of feature extraction and feature selection. The outline followed in this study was to use combinations of feature selection methods, classifications schemes and parameters, in order to determine which combination gives the best results for the specific data, and also which are the most important features for this discrimination.

C. *Feature selection*

Feature selection is a critical step in the learning process, aiming to provide the most accurate training model, by both promoting the features that mostly contribute to class discrimination and by removing those that can undermine it, acting as noise. The feature selection methods used are Correlation Coefficient, ReliefF algorithm, Minimum Redundancy Maximum Relevance algorithm (mRMR) with MID and MIQ schemes, backward greedy search with linear Support Vector Machines Recursive Feature Elimination algorithm (SVM-RFE), Sequential Forward Selection (SFS). There was also the case of selecting all variables (no feature selection). Each feature selection method results in the most important features, ranked ascendingly. Based on this ranking, the top ranked features are inserted iteratively in the feature subset evaluating its performance in terms of classification accuracy with SVM. The feature subset achieving the best performance, was finally used as the outcome of each feature selection method.

D. *Feature classification*

In this study, the discrimination between the two states under investigation (interictal, ictal) was performed by evaluating the CSP features through classification schemes comparison. The classification schemes used in this study are the trivial classifier, Naïve Bayes classifier, k-Nearest Neighbors with k=5, Artificial Neural Networks with 1 hidden layer of 10 nodes. The trivial classifier is used in order to determine the accuracy of random classification, which depends on the prevalence of each class, and serves as a reference point for the performance of the other classifiers. The classification schemes used are summarized and presented in TABLE I.

In order to assess the performance of each classification scheme the performance metrics accuracy, sensitivity and specificity were used which are given by the equations

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

$$Sensitivity = \frac{TP}{TP + FN} \qquad Specificity = \frac{TN}{TN + FP}$$

where *TP* is the true positive, *TN* the true negative, *FP* is the false positive and *FN* the false negative cases.

The classification schemes (combinations of classifier and parameters) were cross-validated in order to evaluate their performance and select the best combination. A standard 10-fold cross validation method was utilized for each classification scheme for testing the performance of each system.

TABLE I. FEATURES AND METHODS USED IN THE ANALYSIS

Extracted Features	19 CSP coefficients δ rhythm 19 CSP coefficients θ rhythm 19 CSP coefficients α rhythm 19 CSP coefficients β rhythm 19 CSP coefficients total power	
Feature selection methods	select all variables Correlation Coeficient, R=0.1 ReliefF mRMR_MID mRMR_MIQ linear SVM-RFE Seq. Forward Selection (SFS)	+SVM for selecting top features
Classification schemes	Trivial classifier Naïve Bayes (NB) classifier Artificial Neural Networks (ANN) with one hidden layer with 10 nodes K-Nearest Neighbors (KNN), K=5	

TABLE II. STUDY POPULATION DEMOGRAPHICS AND SEIZURE TYPES

Patient Code	# seizures	Age	Gender	Epilepsy
PAT_11	1	3	Male	focal right frontal lobe
PAT_13	1	9	Female	focal right frontal lobe
PAT_14	8	7	Female	focal right frontal lobe.
PAT_15	1	13	Male	focal fronto-polar lobe
PAT_24	14	10	Female	focal left frontal lobe
PAT_27	7	13	Male	focal right frontal lobe
PAT_29	1	0	Male	focal bifrontal lobe
PAT_32	1	13	Male	focal right fronto-temporal lobe
PAT_34	28	5	Male	focal right frontal lobe
PAT_35	1	4	Male	focal right frontal lobe
Total seizures	**63**			

III. CLINICAL PROTOCOL AND EXPERIMENTAL PROCEDURE

In this section, the clinical protocol and the experimental procedure is described.

A. Inclusion criteria and ethics

Subjects participating in this study are patients diagnosed with non-idiopathic focal epilepsy. The occurrence of at least one seizure event makes the subject eligible for inclusion in the study. The study's protocol has been approved by the appropriate scientific board of the University Hospital of Heraklion. Informed consent was obtained from all patients following a detailed explanation of the study objectives and protocol to each patient and/or caregiver. All caregivers/patients provided written informed consent prior to being monitored.

B. Procedure

A patient that meets the criteria, as evaluated by an expert neuropediatrician, was admitted to the hospital. Their medical health record were created including clinical data about demographics, medical history, family history, medication, epilepsy classification, etc. An EEG cap with 10/20 electrode system was placed in the head of the patient, a camera was placed opposite the patient's bed and additional sensors for recording the breath rate and SpO2 were utilized. Video and surface EEG were recorded simultaneously for each patient during routine long-term hospital monitoring. The EEG signals were recorded at 19 scalp loci of the international 10–20 system (channels Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2), with all electrodes referenced to the earlobe. An electrode placed in the middle of distance between Fp1 and Fp2 on the subject's forehead served as ground. EEG data were sampled at 256Hz. The long-term EEG recordings were independently evaluated and annotated for epileptic seizures and pathological findings by two expert neuropediatricians.

C. Dataset

The clinical dataset has been recorded at the University Hospital of Heraklion and contained 10 participants (3 females, 7 males). Their age was 7.7±4.4 years at the moment of monitoring. The recorded dataset included 63 seizures in total. The seizures classification into standardized types and subtypes was performed according to the criteria of the International League Against Epilepsy (ILAE) [18]. Table II presents patients demographic data as well as selected clinical data. It should be noted that the dataset contains only cases of focal seizures in order to share similar clinical characteristics.

TABLE III. SUMMARY OF THE 10 BEST FEATURE SELECTION AND CLASSIFICATION COMBINATIONS ALONG WITH THEIR PERFORMANCES

Feature selection method	# of selected variables	Classifier	Classification Accuracy (%)	Sensitivity (%)	Specificity (%)
ReliefF	89	SVM (gk)	91.1	88.7	93.5
CorrCoef, R=0.1	95	SVM (gk)	91.1	88.6	93.6
all variables	95	SVM (gk)	91.1	88.7	93.5
ReliefF	89	KNN, K=5	91.0	89.5	92.5
lin. SVM-RFE	50	SVM (gk)	91.0	88.3	93.7
all variables	95	KNN, K=5	90.9	90.1	91.8
CorrCoef, R=0.1	95	KNN, K=5	90.9	90.1	91.7
mRMR_MID	36	SVM (gk)	90.7	88.2	93.1
SFS	15	SVM (gk)	90.4	87.3	93.5
mRMR_MIQ	37	SVM (gk)	90.2	87.4	93.0
all variables	95	Trivial classifier	50.0		

Note: CorrCoef: Correlation Coefficient, SVM (gk): SVM (Gaussian Kernel), KNN: K-Nearest Neighbors

IV. RESULTS

A. EEG preprocessing

The EEG recordings were digitized in sampling frequency f_s=256 Hz. Artifacts related with subject's activity (body movements, eye blinks, spikes, head movements, chewing, general discharges) contaminate EEG recordings with unwanted noise components. The suppression of the artifacts and the spikes was performed using Independent Component Analysis (ICA).

B. Common Spatial Patterns

The proposed CSP algorithm, as described in the section II.A, was applied on the study's dataset. A sliding temporal window of Δt=2sec and a step of 0.5sec was used. For each temporal window, the 5 EEG rhythms (δ, θ, α, β, total power) timeseries were extracted using bandpass filtering on the specific frequency bands. The CSP features are then extracted

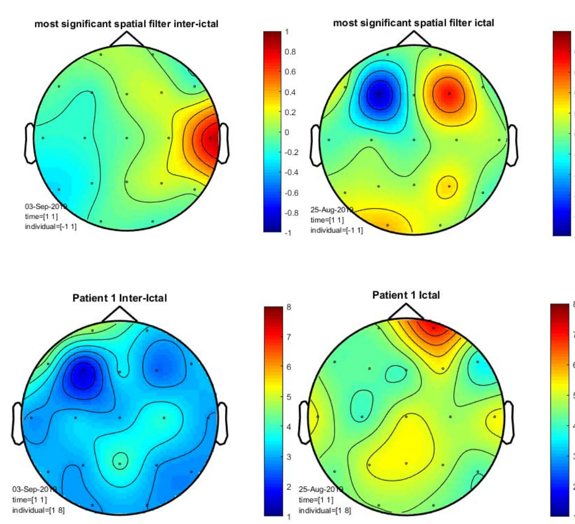

Fig. 1: Interictal (left upper graph) and ictal (right upper graph) most significant spatial filters for the patient (PAT_13). The lower graphs represent the mean CSP features map for interictal (left lower graph) and ictal (right lower graph). The CSP feature map for the ictal period correspond to the seizure locus.

separately for each bandpass filtered timeseries representing corresponding rhythms.

Fig. 1 presents the most significant spatial filters learned by CSP for the first patient in our dataset and represent the most important spatial filters that explain the largest variance of inter-ictal and ictal class. Next we can see the results in the data after applying all the filters that we learned through the training of the CSP algorithm. The scalps show the mean values for all the interictal and ictal data segments of the patient.

The seizure detection problem is highly non-balanced, i.e. data from ictal periods are much fewer than interictal periods, yet a balanced dataset should be ensured for formulating a proper model and increasing its performance. Thus, all samples from ictal and the same samples from interictal periods were selected for the subsequent analysis. These procedures lead to a feature matrix X [984x95] of 984 time window cases for each class and 19 channels x 5 rhythms = 95 features. Specifically, the columns of X are (19 features for δ, 19 for θ, 19 for α, 19 for β and 19 for total spectrum) and the rows represent the temporal window EEG segment samples.

Then, the feature selection was applied aiming to find the optimal feature subset for improving discrimination ability. The automatic feature selection methods used are the CorrCoef (with R=0.1), the ReliefF, the mRMR (MID and MIQ criteria), the backward greedy search with linear SVM-RFE and the Sequential Forward Selection (SFS). The top ranked features were inserted iteratively in the feature subset evaluating each candidate subset's performance in terms of 10-fold SVM classification accuracy used as the objective function. This procedure revealed that for the problem under investigation, the best feature selection method was ReliefF selecting a features subset of 89 features from the feature set.

Then, the classification phase was applied. The trivial classifier's accuracy was 50%, defining the random classification accuracy. The best accuracy was achieved with the ReliefF algorithm, the SVM classifier (with Gaussian kernel) and 10-fold cross-validation achieving classification of 91.1%.

V. Discussion

The aim of this study is to develop a seizure detection model based on CSP features. An issue in the area of seizure detection using EEG signal analysis is that information from the multivariate signals coming from different EEG channels should be taken into account in order to discriminate a possible ictal period. This information presented in EEG head maps that can be represented using specific coefficients is very useful towards this direction.

The CSP method is an advanced multivariate signal processing method using spatial filters in order to extract meaningful spatial coefficients that describe cerebral activity. These CSP features using automatic feature selection and classification techniques led to a best achieved time-window classification of 91.1% using the combination ReliefF and SVM (Gaussian Kernel) and 10-fold cross validation. These results indicate that CSP features could be used in combination with other feature for seizure detection, although their effectiveness might be improved. In the future, we propose to combine the 19-channel CSP features of each rhythm in a specific metric that will represent the underlying EEG map with the appropriate normalizations needed.

Acknowledgment

The authors would like to thank Spyridon Voutoufianakis, neuropediatrician, for the seizure annotation and Giorgos Livas for his valuable technical support.

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