A Channel Selection Method for EEG Classification based on Exponentially Damped Sinusoidal Model and Stochastic Relevance Analysis

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Abstract: This work introduces a new methodology to select EEG channels related to epileptic seizures by electroencephalogram (EEG) rhythms extraction. Rhythms extraction is an alternative to extract useful information from specific band frequencies, analyze changes in the EEG signals, and detect brain abnormalities. In this approach, the EEG signals are modeled by Exponentially Damped Sinusoidal model (EDS) and the EEG rhythms extraction is based on Stochastic Relevance Analysis (SRA). Achieve results show that EDS model combined with a stochastic relevance measure is a proper alternative for EEG classification of epileptic signals and also could be used for EEG channel selection with seizure activity. The effectiveness of this approach is compared in each experiment with other well known method for feature extraction called as Rhythmic Component Extraction (RCE). This comparison was done based on the performance of the k-NN classifiers and the channels selected were validated by visual inspection and topographic scalp map. The study uses real and multi-channel EEG data and all the experiments have been supervised by an expert neurologist. We conclude that the proposed scheme is a suitable approach for automatic seizure detection at a moderate computational cost, also opening the possibility of formulating new criteria to select, classify or analyze abnormal EEGs channels.

1 INTRODUCTION

Electroencephalographic signals (EEG) contain useful information about the condition of the brain state and their analysis is important to extract hidden information or features that the human cannot directly detect by visual inspection. Moreover, EEG signals with epilepsy change continuously and to process every EEG channel requires a long period of time, more visual analysis, high storage databases, and more computational cost. To improve the efficiency in EEG processing it is necessary to deal with multi-channel processing and highlight the most pertinent features of the signal. This allows to identify and extract EEG rhythms faster, and also to see which parts of the brain are the most affected for some abnormality.

Several authors have shown that epileptic seizures could be decomposed into one or more components. For example, the typical pattern or ictal rhythm in mesial temporal lobe epilepsy appears as a high voltage blunt or sharp $5-7$ Hz theta rhythm over one temporal region (Nam et al., 2002). Other authors show a principal epileptic track in band frequency range between $2-7$ Hz (Guerrero-Mosquera et al., 2010). Therefore, EEG rhythms extraction could be used in detecting brain abnormalities such as epilepsy disease.

There are different approaches propose in the literature for extracting EEG rhythms, such as wavelet decomposition (Zalay et al., 2009), Independent Component Analysis (ICA) (Sri and Rajapakse, 2008), adaptive schema (Veluvolu et al., 2012), multidimensional decomposition (Orekhova et al., 2011) and frequency dominant characterization (Lodder and Putten, 2011). Most of these studies are only focused on finding the onset and duration of the rhythm, present many parameters to validate, show a dependency with frequency resolution, but do not reflect the true peak amplitude of the posterior dominant rhythm.

Other well know technique is the Rhythmic Component Extraction (RCE), which combines multichannel signals with weights that are optimally sought

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for such that the extracted component maximally contains the power in the frequency range of interest and suppresses that in unnecessary frequencies[1]. Other methods proposed at the state-of-the-art need to validate many parameters or demand computational cost in training (Peters et al., 2001; Yang et al., 2012; Duun-Henriksen et al., 2012).

In this paper, we introduce a new method for EEG channel selection based on Exponentially Damped Sinusoidal model (EDS) and Stochastic Relevance Analysis (SRA). Our approach distinguishes variables that represent effectively a "hidden" phenomena according to stochastic variability measure, that is used as relevance function (Sepulveda-Cano et al., 2011), and detects the EEG channels with more seizure activity. The effectiveness of our approach is compared with RCE method both for EEG segment classification problems and EEG channel selection. The classifier used is the well known k-nearest neighbor (k-nn) algorithm.

This paper is organized as follows: Section 2 introduces the EDS model and the Stochastic Relevance Analysis (SRA). Section 3 describes the EEG databases and the experiments setup, and finally in Section 4 and Section 5, the main results are discussed and the principal conclusions with further work are presented.

2 PROCESSING METHODS

The proposed method is based on two main steps: (1) EEG is modeled by Exponentially Damped Sinusoidal model (EDS), and (2) EEG rhythms are extracted by Stochastic Relevance Analysis (SRA). Both methods are briefly explained as follows.

2.1 Exponentially Damped Sinusoidal Model (EDS)

EDS model represents an EEG signal as a finite sum of p discrete-time exponentially damped complex sinusoids:

$$x(n) = \sum_{i=1}^{p} a_i \exp(j\phi_i) \exp((-d_i + j2\pi f_k)n\Delta t) + \varepsilon(n) \qquad n = 0, 1, \ldots, N-1$$

where $n\Delta t$ is the time lapse between the origin and the sample $x(n)$, Δt is the sampling interval, and $\varepsilon(n)$ is Gaussian white noise. The parameters of this model are the amplitudes a_i, the phases ϕ_i, the damping factors d_i, and the frequencies f_i. Since EDS are a set of basis functions, they can be used to model any arbitrary signal sufficiently closely, assuming that the model order is high enough. Present study addresses the problem of estimating the model parameters when the EEG signal is embedded in noise by using the subspace–based exponential data fitting proposed in (De Clercq et al., 2005), where EEG signal is stacked in Hankel data matrix. Then, the model parameters needed in Eq. (1) are estimated by Singular Value Decomposition (SVD). More detail of EDS parameters estimation in (De Clercq et al., 2005).

[1]More details of RCE algorithm in (Tanaka and Saito, 2008)

2.2 Stochastic Relevance Analysis (SRA)

Relevance analysis distinguishes variables that represente effectively the subjacent physiological phenomena according to some evaluation measure. Such representative variables are named *relevant features*, whereas the evaluation measure is known as *relevance measure*. Variable selection tries to reject those variables whose contribution to representation target is none or negligible (*irrelevant features*), as well as those that have repeated information (*redundant features*). Thus, the first objective concerning the variable selection stage is to define the concept of relevance (Sepulveda-Cano et al., 2011). Let the set of objects $\mathscr{S}_s = \{\boldsymbol{S}_k, k = 1, \ldots, M\}$ with M observations described by a set of features s_{ij}. In addition, each sample is associated with one and only one element of the set of class labels $\boldsymbol{c} = \left\{c^{(k)} \in \mathbb{N} : k = 1, \cdots, K\right\}$, where K is the number of classes to be considered. Then, given $\mathscr{S}_s$, and for any feature s_{ij}, the relevance function ρ is defined as:

$$\begin{aligned} &\rho : \mathbb{R}^{1\times T} \longrightarrow \mathbb{R} \\ &(\mathscr{S}_s, s_{ij}) \mapsto \rho(\mathscr{S}_s, s_{ij}) \in \mathbb{R} \end{aligned} \qquad (1)$$

where the relevant function ρ satisfies the following properties (Sepulveda-Cano et al., 2011):

- *Non-negativity*, $\rho(\mathscr{S}_s, s_{ij}) \geq 0$, for all i.
- *Nullity*, the function $\rho(\mathscr{S}_s, s_{ij})$ is null if feature s_{ij} has not relevance at all.
- *Non-redundancy*, if $s'_{ij} = \lambda s_{ij} + \eta$, where the real-valued $\lambda \neq 0$, y η is some noyse with zero mean and unit variance, then, $\left|\rho(\mathscr{S}_s, s'_{ij}) - \rho(\mathscr{S}_s, s_{ij})\right| \to 0$

It is assumed that higher weights are associated with the most relevant features. This work considers the following unsupervised measure of relevance:

c. *Stochastic Variability:* the time-varying relevance measure is evaluated:

$$\rho_{\upsilon}(\boldsymbol{S}_y;\tau) = [\chi(1) \cdots \chi(\tau) \cdots \chi(pT)]^{\top}, \quad (2)$$

where $\chi(\tau) = \mathscr{E}\{|\lambda_j^2 v_j(\tau)|\}$, $\{\lambda_j : j = 1,\ldots,q\}$ is the set of most relevant eigenvalues of the matrix $\boldsymbol{S}_y$, and the scalar $v_j(\tau)$ is the respective element in the instant τ, and $\tau = 1,\ldots,pT$ indexes each of the relevance values calculated for the entire set of time-varying data. To determine the relevance related to each of the stochastic variables, the Eq.(2) can be arranged to the relevance matrix $[\rho_{\upsilon 1}(\boldsymbol{S}_y;t)\cdots\rho_{\upsilon f}(\boldsymbol{S}_y;t)\cdots\rho_{\upsilon F}(\boldsymbol{S}_y;t)]^{\top}$, where each row $\rho_{\upsilon f}(\boldsymbol{S}_y;t) = [\chi((f-1)T+1)\ldots\chi(t)\ldots\chi(fT)] \in \mathscr{R}^{T\times 1}$ shows the contribution of the $\boldsymbol{s}_{ri}$ stochastic feature along fixed time moments.

3 MATERIAL AND SETTING

This work uses two EEGs databases: one of them (labeled as DB1), described in detail in (Guerrero-Mosquera et al., 2010), consists in 6 adult epileptic patients obtained in a restful wakefulness stage and recorded at the *Clinica Universitaria de Navarra, Department of Neurophysiology* (Pamplona, Spain). All of them contained focal epileptiform activity, according to experienced neurologists. We used 6 EEG recordings of 24 *min* length taken from 23-th, 24-th and 25-th channels using the 10- 20 International System of Electrode Placement with additional anterotemporal electrodes T1/T2. In practice, raw EEG were filtered by a digital low-pass filter with cut-off frequency of 20 Hz, sampled frequency of 200 Hz and ocular artifacts rejected by Independent Component Analysis (Guerrero-Mosquera and Navia-Vazquez, 2012).

The other database (labeled as DB2) is a collection recorded at the *Instituto de Epilepsia y Parkinson del Eje Cafetero* (Pereira,Colombia). Each data set from 35 patients contains 160 recorded scalp EEG signals from 23-th, 24-th and 25-th channels corresponding to electrodes placed on the head according to the International 10-20 System of Electrode Placement Standard. Set *A* holds 80 recordings labeled as normal (seizure–free), whereas set *E* holds 80 recordings labeled as having epilepsy (epileptiform activity by neurologist). Recordings have been sampled at a frequency of 256 Hz, with 12 *bits* resolution and a 2-*min* duration. All patients underwent clinical examination by neurologist. The data had been acquired in a non–regulated conditions, and the noised data holds, besides awake background EEG activity, the muscle artifacts as well as 60 Hz power line interference.

3.1 Experimental Setup

Fig.1 summarizes the experimental outline proposed: *a*) EEG is modeled by EDS and pre-processed following (De Clercq et al., 2005); *b*) EEG rhythms are obtained by Stochastic Relevance Analysis (SRA) and RCE method; and *c*) Classifier performance and relevant channels are obtained to determine the presence of epilepsy. The selected channels will be evaluated both visual inspection by expert neurologist and electrode placement on topographic map.

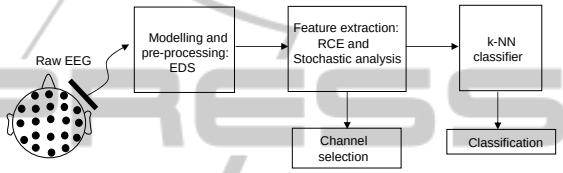

Figure 1: A general scheme with the proposed method for EEG classification and scalp localization of seizure activity.

EDS model uses four parameters: d determining which left singular vectors belong to the signal subspace, N samples, and Hankel matrix dimension $L \times M$. The values used here corresponds to the values suggested in (De Clercq et al., 2005) were $N = 30720$, $L = N/2 = 15371$, $M = L-1 = 15370$ and $d = 0.01$. It was observed by visual inspection that this method successfully had removed muscle artifact while the epileptic activity had been enhanced.

In this work, we attempt to extract the frequency band between 0.5 and 8 Hz, which is the most closely related to epilepsy (Nam et al., 2002; Guerrero-Mosquera et al., 2010). All experiments proposed in this work use real and multi-channel EEG data and have been supervised by an expert neurologist. Regarding the relevance measure, both RCE and stochastic variability are used to find the EEG channels with greater relevance weight in presence of epileptic seizure and then finding approximately the damaged brain region.

Each rhythm is used as a dynamic feature for the classifier training. After obtaining the feature matrix, Principal Component Analysis (PCA) is used as a feature extraction method to reduce the high dimensionality of the feature matrix. The number of principal components (PCs) is selected based on the number of PCs that maximizes the performance measures in the classifier. Cross-validation procedure is used to evaluate the performance of proposed experiments, which consists in dividing the database into 10 folds, each one with an equal number of signals per class. A

$k-$ nearest neighbors (k-nn) classifier is trained with $k = 5$. The classification performance is measured by means of the accuracy, sensitivity and specificity, defined by:

$$A_{cc}(\%) = \frac{N_c}{N_T} * 100$$

$$Sens(\%) = \frac{N_{TP}}{N_{TP} + N_{FN}} * 100;$$

$$Spec(\%) = \frac{N_{TN}}{N_{TN} + N_{FP}} * 100;$$

where N_c is the number of correctly classified patterns, N_T is the total number of patterns used to feed the classifier, N_{TP} is the number of true positives (objective class accurately classified), N_{FN} is the number of false negatives (objective class classified as reference class), N_{TN} is the number of true negatives (reference class classified as objective class), and N_{FP} is the number of false positives (reference class classified as objective class).

Table 1: Accuracy values for each EEG channel by Stochastic Relevance Analysis (SRA) for all patients (DB1). Values in bold type are those selected by neurologist through a visual inspection. Note the correspondence between high values obtained by SRA and EEG channels chosen by visual inspection.

EEG	Patient		EEG	Patient	EEG	Patient		
	1	2		3		4	5	6
F4	0.16	0.06	Fp1	0.19	F4	0.59	0.27	0.66
FP2	0.46	0.06	F3	0.08	Fp2	0.14	0.13	0.49
F3	0.43	0.20	C3	0.11	F3	0.32	0.11	0.40
FP1	0.18	0.36	P3	0.05	Fp1	0.18	0.15	0.41
T6	0.31	0.09	O1	0.04	T6	0.50	0.24	0.31
T5	**0.98**	0.15	F7	0.06	T5	0.20	0.14	0.36
O2	0.48	0.45	T3	0.36	O2	0.11	0.01	0.29
O1	0.62	0.31	T5	0.19	O1	0.26	0.07	0.20
F7	0.82	0.32	Fp2	0.17	F7	**0.77**	0.11	0.39
F8	0.58	**1.00**	F4	0.11	F8	0.25	**0.48**	**0.74**
T3	**0.98**	0.15	C4	0.46	T3	0.13	**0.70**	0.32
T4	0.22	**0.75**	P4	0.18	T4	0.89	0.05	**0.84**
C4	0.51	0.47	O2	0.16	C4	0.20	0.03	0.20
C3	0.35	0.15	F8	0.32	C3	0.21	0.06	0.21
P4	0.75	0.16	T4	**1.00**	P4	0.27	0.23	0.25
P3	0.59	0.12	T6	**0.88**	P3	0.07	0.15	0.29
Cz	0.77	0.42	Fz	0.17	Cz	0.69	0.14	0.15
Ecgp	0.11	0.01	Cz	0.15	Ecgp	0.6	0.01	0.08
Pz	0.85	0.59	Pz	0.13	Pz	0.40	0.18	0.38
T1	**1.00**	0.15	A1	0.10	T1	**1.00**	**1.00**	0.13
T2	0.29	**0.63**	A2	**0.72**	T2	0.08	0.09	**1.00**
Fz	0.47	0.53	Ecg1	0.02	A1	**0.84**	**0.91**	0.59
Ecgn	0.04	0.03	T1	0.21	A2	0.34	0.12	**0.82**
			T2	0.13	Fz	0.25	0.22	0.62
					Ecgn	0.01	0.01	0.07

4 RESULTS

This section shows the effectiveness of the methodology proposed by comparing the approach with Rhythmic Component Extraction (RCE) in two sceneries: channel selection and EEG classification.

4.1 Channel Selection

Table 1 shows the estimated stochastic relevance values for each EEG channel (DB1 data), computed by SRA. Values in bold type are those selected by neurologist through a visual inspection. Note the correspondence between high values obtained by SRA and EEG channels chosen by visual inspection.

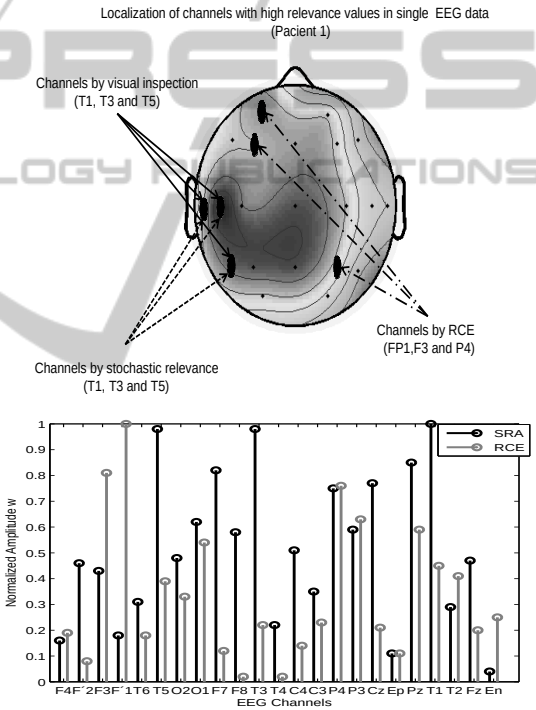

Figure 2: Comparison of the channels selected by RCE, stochastic relevance (SRA) and visual inspection at patient 1 (DB1 database). Upper: Localization of the channels selected on scalp topographic map. Black areas represent a highest energy concentration than grey areas. Bottom: Relevance values obtained by RCE method and stochastic relevance for each channel. Note that EEG channels with high weighting by stochastic relevance (bottom) correspond to channels located on epileptogenic region (upper).

Fig. 2 (upper) shows corresponding channels selected by RCE and stochastic relevance (SRA) with the visual inspection on scalp topographic map at patient 1 (DB1). It can be seen that high values achieved by RCE method do not correspond to channels chosen by the neurologist through visual inspection. The Fig. 2

(bottom) depicts relevance values obtained for each DB1 channel at the patient 1 by RCE method and stochastic relevance. Note that SRA measures successfully selects the channels with more seizure activity (T1, T3 and T5) showing high relevance values close to 1. All results show that our method provide a better medical interpretability about epileptic region compared to the weights computed by RCE method. Shortest weights values corresponding to EEG derivations are discarded in this figure.

4.2 EEG Segment Classification

Table 2 shows classification results achieved in DB1 and DB2 databases by RCE and stochastic variability (SRA). As seen from Table 2, there is an improvement in terms of classifier performance when we use stochastic relevance, DB1 achieves 95.38% and DB2 achieves 94.60% in accuracy values, compare to RCE that present accuracy values for DB1 (93.60%) and DB2 (92.10%).

Table 2: Comparison in classification performance of RCE and SRA by method by *k*-NN algorithm.

Method	DB	Acc(%)	Sens(%)	Spec(%)
RCE	DB1	93.60	93.60	93.60
	DB2	92.10	93.85	90.35
SRA	DB1	95.38	95.90	96.23
	DB2	94.60	94.60	94.32

Note that values in classifier performance are close each to other, even though DB2 is more contaminated by artifacts than DB1, which has a preprocessing to eliminate ocular movements (Guerrero-Mosquera and Navia-Vazquez, 2012). The proposed model is then stable for EEG classification problems in presence of noise.

5 CONCLUSIONS AND FUTURE WORK

A method for classification and channel selection for EEG multi-channel data with epilepsy is proposed. This method, based on Exponentially Damped Sinusoidal model (EDS) and Stochastic Relevance Analysis (SRA), is simple and do not requires high computational cost in training than others methods proposed at the state-of-the-art (Peters et al., 2001; Yang et al., 2012; Duun-Henriksen et al., 2012). Achieved results show this method is an alternative for extracting relevant EEG rhythms and selecting EEG channels with epileptic activity. Results validated by experts through visual inspection and scalp topographic map, show that the approach also provides a better medical support in epileptic region localization.
Future work includes: comparing our approach with other seizure detection methods proposed in the state-of-the-art; exploring other brain abnormalities such as Alzheimer, sleep disorders and dementia; exploiting the features for epileptogenic region analysis, and consider the feasibility of our method to seizure anticipation.

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