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Stochastic relevance analysis of epileptic EEG signals for channel selection and classification

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***Abstract*— Time-frequency decompositions (TFDs) are well known techniques that permit to extract useful information or *features* from EEG signals, being necessary to distinguish between irrelevant information and the features effectively representing the subjacent physiological phenomena, according to some evaluation measure. This work introduces a new method to obtain relevant features extracted from time-frequency plane for epileptic EEG signals. Particularly, EEG features are extracted by common spectral methods such as short time Fourier transform (STFT) , wavelets transform and Empirical Mode Decomposition (EMD). Then, each method is evaluated by Stochastic Relevance Analysis (SRA) that is further used for EEG classification and channel selection. The classification measures are carried out based on the performance of the *k*-NN classifier, while the channels selected are 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. Results obtained in this paper show that SRA is a good alternative for automatic seizure detection and also opens the possibility of formulating new criteria to select, classify or analyze abnormal EEG channels.**

***Index Terms*— Time-frequency analysis, EEG, epileptic seizure detection, feature extraction, relevance Analysis.**

I. INTRODUCTION

Electroencephalographic (EEG) signal processing provides new insights to analyze, in more detail, the cortical activity during the evaluation of different clinical disorders related to epileptic seizures, some of which include quantitative measures extracted from EEG signals, feature extraction, and machine learning methods. Several authors have shown that epileptic seizures can be decomposed into one or more physical components, i.e., typical patterns or ictal rhythms in mesial temporal lobe. Particularly, epilepsy appears as a high voltage blunt or sharp $2-7$ *Hz* theta rhythm over one temporal region [1], [2]. Thus, EEG rhythm extraction can be of benefit in detecting brain abnormalities such as epilepsy.

Different time–frequency (*t*–*f*) and time-varying approaches have been proposed with the aim to follow the modification of the EEG spectra during epileptic seizure states, grounded on their discriminating capability of frequency bands of EEG activity between normal and ictal patients. In this way, there are different approaches proposed for extracting EEG rhythms and spectral sub-band methods, such as wavelet decomposition [3], Independent Component Analysis (ICA) [4], adaptive schemes [5], multi-dimensional decomposition [6], and frequency dominant characterization [7], among others. Nevertheless, all the extracted features from enhanced t-f representations are analyzed by static statistical approach and single EEG channel analysis, hence, there is a missing a valuable information about the time-evolving EEG process.

To improve the efficiency in EEG processing, in addition to deal with multi-channel selection and highlight also the most pertinent features of the EEG Data, it is necessary also to see which parts of the brain are the most affected by some abnormality. In this regard, weighted multi-channel EEG data combination is discussed in [8], where component maximally containing the power in the frequency range of interest is extracted along with suppression of unnecessary frequencies. Other proposed approaches of multi-channel selection have been proposed, namely, [9], [10], [11]. However, since EEG signals with epilepsy change continuously and to process every EEG channel requires a long period of time, the extracted data might be processed as stochastically dependent, and thus, to apply a relevance measure capable of capturing the dynamic information and keep valuable information missed from time-evolving EEG analysis.

In this paper, we introduce a new relevance measure for EEG classification and channel selection based on Stochastic Relevance Analysis (SRA) [12] . The paper shows as SRA distinguishes variables that represent effectively a "hidden" phenomena according to stochastic variability measure, and how these relevance measures could be used as a relevance function to detect EEG channels with more seizure activity. The effectiveness of our approach is presented for both EEG segment classification problems and EEG channel selection and is also tested for Short Time Fourier Transform (STFT) and Wavelet transform (Wt). The classifier used is the well known *k*-nearest neighbor (*k*-nn) algorithm.

II. PROCESSING METHODS

The proposed method comprises the following two steps: *i*) Feature extractions from the enhanced EEG data by using a given time-variant spectral methods (EMD, wavelet and STFT), *ii*) Relevance analysis by the SRA, and *iii*) EEG classification or channel selection (see Fig.1).

A. Rhythm extraction from enhanced EEG data

a) Short–Time Fourier Transform: The main goal in time–variant decomposition is to separate the signal spectrum into their constituent subspectral components, from which the time–evolving rhythms are to be further estimated. The

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STFT introduces a time localization by using a sliding window function, $\phi(t)$, going along with the signal $y(t)$, that is, $Y_\phi(f) = \int_{-\infty}^{\infty} y(t)\phi_{a,b}(f,t)dt$. So, the spectral density of $y(t)$, on the time–frequency plane, can be calculated by means of the *spectrogram*:

$$S_y(t,f) = \left|\int_T y(\tau)\phi(\tau-t)e^{(-j2\pi f\tau)}d\tau\right|^2, S_y(t,f)\in\mathbb{R}^+ \quad (1)$$

b) Wavelet Transform: This transformation is grounded on the basis functions, constructed from shifted and scaled versions of a given mother function $\phi(t)\in L^2(\mathbb{R})$, keeping the energy concentrated on short intervals of time–frequency plane. The WT spectral density, equivalent to Eq. (1), is performed by making time–frequency atoms, as follows: $\phi_{a,b}(t) = a^{-1/2}\phi\left((t-b)/a\right)$, with $a\in\mathbb{R}^+, b\in\mathbb{R}$. Thus, the WT of a given function $y(t)$ is defined as:

$$WT\{y(t)\} = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} y(t)\phi^*\left(\frac{t-b}{a}\right)dt \quad (2)$$

Since WT can be expressed by the Fourier Transform as $WT\{y(t)\} = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} Y(\omega)\Phi^*(a\omega)e^{jb\omega}d\omega$, then, it follows that the WT is a smoothed version of the Fourier spectrum, $Y(\omega)$. In conclusion, the spectral bandwidth of the WT can be changed, and hence, the time resolution adjusts to information speed, being this property the most significant advantage of WT in the time varying spectral analysis.

c) Empirical Mode Decomposition: This adaptive method aims at decomposing a given data into $p\in\mathbb{N}$ finite and often small number data–driven basis $z_i(t)$, termed intrinsic mode functions (IMF) for which the instantaneous frequency can be defined everywhere. The signal $y(t)$ is represented by EMD, as follows:

$$y(t) = \sum_{i=1}^{p} z_i(t) + r_p(t)$$

where resultant components $\{z_i(t)\in\mathbb{R}\}$, which are symmetric with respect to the local mean value and have the same numbers of zero crossings and extremes, are generated by sifting iteratively the input data, that is, $z_i(t) = r_{i-1} - r_i(t)$; and $r_p(t)$ is the final residue, with only one maxima and one minima from which no more IMF can be derived.

B. Stochastic Relevance Analysis (SRA)

Instead of a widely used scalar–valued parameter set extracted from the EEG signal, the EEG events, such as epileptic seizures, are detected by using a vector set of time–variant rhythm waveforms, $\{\boldsymbol{x}_n\in\mathbb{R}^{1\times T} : n\in p\}$, with, $t\in T$, which carries temporal information of the non–stationary EEG recordings. To analyze the discriminant capability of EEG rhythmic activities on the seizure detection, priority is placed on identifying the time evolution and structure of the underlying subseries, and how they contribute to the performance system. In other words, the contribution of each rhythm must be analyzed and quantified carefully [13]. In this regard, relevance analysis of input spaces is to be carried out, being latent variable techniques widely used for this aim that finds a transformation mapping p–dimensional stochastic waveform arrangement, $\boldsymbol{\Xi}\in\mathbb{R}^{p\times T}$, into p–dimensional stochastic set, $\widehat{\boldsymbol{\Xi}}\in\mathbb{R}^{p\times T}$, in such a way that the data information is maximally preserved. Besides, as the relevance function, $g\in\mathbb{R}$, the evaluation measure of transformation is given that distinguishes variables effectively representing the subjacent physiological phenomena.

The stochastic waveform set, $\{\boldsymbol{x}_i\}$, is represented by the observation assemble comprising N objects that are disposed in the input observation matrix $\boldsymbol{X}_{\boldsymbol{\Xi}} = [X_1|\cdots|X_i|\cdots|X_N]$. In turn, every object, denoted as $X_i, i = 1,\ldots,N$, is described by the respective observation set of time–variant vectors, $\{\boldsymbol{x}_{ji}\subset\boldsymbol{\Xi}, j = 1,\ldots,p\}$, such that, $X_i = [\boldsymbol{x}_{1i}|\cdots|\boldsymbol{x}_{ji}|\cdots|\boldsymbol{x}_{pi}]^\top$, $X_i\in\mathbb{R}^{p\times T}$, where vector $\boldsymbol{x}_{ji} = [x_{ji}(1)\ldots x_{ji}(t)\ldots x_{ji}(T)]$ is each one of the measured time–variant rhythms from EEG recordings, equally sampled evolving through time, and being $x_{ij}(t)$, the j–th stochastic waveform for the i–th object upon a concrete t instant of time. Given $\boldsymbol{X}_{\boldsymbol{\Xi}}$, there will be a couple of orthonormal matrixes, $\boldsymbol{U}\in\mathbb{R}^{N\times N}, \boldsymbol{V}\in\mathbb{R}^{pT\times pT}$, plus diagonal matrix $\boldsymbol{\Sigma_X}$, as well, so that a simple linear decomposition takes place, i.e., $\boldsymbol{X}_{\boldsymbol{\Xi}} = \boldsymbol{U}\boldsymbol{\Sigma_X}\boldsymbol{V}^\top$, where $\boldsymbol{\Sigma_X}\in\mathbb{R}^{pT\times pT}$ holds p ordered eigenvalues ν of $\boldsymbol{X}_{\boldsymbol{\Xi}}$. The least mean squared–based error is assumed as the evaluation measure of transformation, $g(\boldsymbol{X}_{\boldsymbol{\Xi}},\widehat{\boldsymbol{\Xi}}) \sim \min\mathscr{E}\{\|\boldsymbol{\Xi}-\widehat{\boldsymbol{\Xi}}\|_2\}$, (being $\mathscr{E}\{\cdot\}$ the expectation operator), that is, the maximum variance is preferred as relevance measure, when the following covariance matrix estimation is carried out [12]:

$$\mathrm{cov}\{\boldsymbol{X}_{\boldsymbol{\Xi}}\} = \boldsymbol{X}_{\boldsymbol{\Xi}}^\top\boldsymbol{X}_{\boldsymbol{\Xi}} = \boldsymbol{V}\boldsymbol{\Sigma}_{\boldsymbol{X}}^2\boldsymbol{V}^\top \quad (3)$$

To make clear the contribution of each time–variant value $x_{ij}(t)$, expression (3) can be further extended in the form, $\boldsymbol{X}_{\boldsymbol{\Xi}}^\top\boldsymbol{X}_{\boldsymbol{\Xi}} = \sum_{j=1}^{p}\nu_j^2 V_j V_j{}^\top$, where V_j is the j–th column of matrix $\boldsymbol{V}$. Consequently, the amount of relevance captured at every moment t by the singular value decomposition, associated with the whole set of waveforms, is assessed as the following time–variant relevance measure:

$$g(\boldsymbol{X}_{\boldsymbol{\Xi}},\widehat{\boldsymbol{\Xi}};t) = \sum_{j=1}^{p}|\nu_j^2 V_j|, \quad (4)$$

This relevance measure is capable of capturing the stochastic information and is valid for considered cases of pathology diagnosing from biosignal signals, for example, EEG epileptic recordings.

III. Experimental Setup

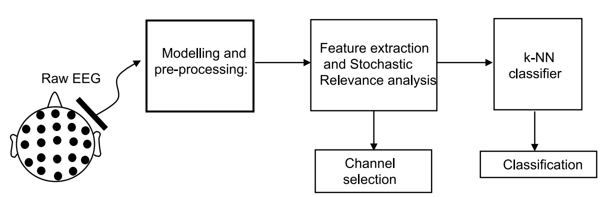

Fig. 1. A general scheme with the proposed approach for EEG classification and scalp localization of seizure activity.

Fig.1 summarizes the experimental outline of proposed approach: *a*) EEG data is enhanced by spectral methods;

b) relevance coefficients are obtained by the SRA; and *c*) classifier performance and channel selection are carried out to determine the presence of epilepsy. The selected channels are evaluated by both visual inspection of expert neurologist and electrode placement on a topographic map.

A. EEG Database and setup

This work uses two EEG databases: the first one (termed as DB1) holds six adult epileptic patients in a restful wakefulness stage and recorded at the *Clinica Universitaria de Navarra, Department of Neurophysiology* (Pamplona, Spain) [2]. The second collection (termed as DB2), which had been recorded at the *Instituto de Epilepsia y Parkinson del Eje Cafetero* (Pereira, Colombia) from 35 patients, holds 160 recorded scalp EEG signals (lasting 2-*min*) 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. For both data collections, recordings were acquired at a sampling frequency of 256 *Hz*, with 12 *bits* resolution and all patients underwent clinical examination by neurologist.

B. EEG feature extraction

In this work, we attempt to extract the frequency band between 0.5 and 8 *Hz*, which is the most closely related to epilepsy [1], [2]. This is accomplished using the time frequency decomposition methods.The spectral decomposition methods were adjusted as follows: STFT with Gaussian sliding window with 2.9 *s* [12], wavelets used a mother wavelet (Db6) and 6 decomposition levels matching with the set of needed frequency band boundaries according to the aproach described in [14].The number of decomposition levels for EMD were 8, using only those IMF's that match with the desired band.

Once extracted the band of 0.5 -8 *Hz* of each channel, the relevance analysis is performed to determine the relevance of channels with greater weight and influence of epileptic seizure and then finding approximately the damaged brain region. That band 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. For this purpose, a k-nearest neighbors (k-nn) classifier is employed, with $k=5$. Lastly, cross-validation procedure is used to evaluate the performance of the proposed experiments, which consists in dividing the database into 10 folds, each one with an equal number of signals per class. The performance is measured by means of the accuracy, sensitivity, and specificity [2].

IV. Results

A. EEG Segment Classification

Table I shows classification results achieved with SRA for DB1 and DB2 databases. Note that there is a high performance classification with each method, STFT achieves 98.50% and 95.62% with DB1 and DB2 respectively; wavelets (WT) achieves 97.44% for DB1 and 94.26% for DB2; and EMD achieves 97.85% for DB1 and 94.96% for DB2. These results show the effectiveness of SRA as a relevance measure for time-frequency features. Also note that the values in classifier performance are close to each other, even though DB2 is more contaminated by artifacts than DB1, which has a pre-processing to eliminate ocular movements [15]. The proposed model becomes then stable for EEG classification problems in the presence of noise.

TABLE I

EEG segment classification

		***k*-nn Classifier Performance**		
	Method	*Accuracy(%)*	*Sensitivity(%)*	*Specificity(%)*
DB1	STFT	98.50 ± 2.57	98.08 ± 4.20	98.92 ± 3.06
	WT	97.44 ± 1.65	98.87 ± 0.41	97.00 ± 3.16
	EMD	97.85 ± 0.42	97.56 ± 1.31	98.79 ± 0.74
DB2	STFT	95.62 ± 1.35	94.24 ± 2.26	95.56 ± 3.28
	WT	94.26 ± 1.89	95.37 ± 2.54	94.36 ± 2.65
	EMD	94.96 ± 1.68	95.32 ± 2.36	92.12 ± 2.53

B. Channel Selection

TABLE II

Relevance measures for each EEG channel by STFT+SRA.

EEG	Patient 1	Patient 2	**EEG**	Patient 3	**EEG**	Patient 4	Patient 5	Patient 6
F4	0.33	0.63	Fp1	0.19	F4	0.29	0.23	0.62
FP2	0.36	0.50	F3	0.08	Fp2	0.33	0.14	0.49
F3	0.44	0.21	C3	0.32	F3	0.24	0.31	0.17
FP1	0.44	0.24	P3	0.37	Fp1	0.45	0.15	0.41
T6	0.37	0.45	O1	0.39	T6	0.33	0.34	0.31
T5	**0.76**	0.25	F7	0.28	T5	0.36	0.14	0.54
O2	0.38	0.45	T3	0.36	O2	0.11	0.36	0.36
O1	0.39	0.27	T5	0.19	O1	0.26	0.45	0.28
F7	0.40	0.28	Fp2	0.17	F7	**0.87**	**0.48**	0.37
F8	0.27	**1.00**	F4	0.72	F8	0.37	0.21	**0.74**
T3	**0.86**	0.29	C4	0.72	T3	0.63	**0.70**	0.39
T4	0.23	**0.75**	P4	0.68	T4	0.39	0.17	**0.84**
C4	0.25	0.47	O2	0.57	C4	0.42	0.23	0.17
C3	0.73	0.31	F8	0.44	C3	0.21	0.26	0.21
P4	0.37	0.16	T4	**1.00**	P4	0.45	0.33	0.25
P3	0.72	0.35	T6	**0.86**	P3	0.60	0.17	0.29
Cz	0.68	0.37	Fz	0.44	Cz	0.69	0.24	0.55
Pz	0.57	0.45	Cz	0.41	Pz	0.70	0.17	0.48
T1	**1.00**	0.50	Pz	0.40	T1	**0.77**	0.18	0.17
T2	0.22	0.57	A1	0.10	T2	0.45	**1.00**	**0.77**
Fz	0.41	**0.68**	A2	**0.76**	A1	**0.84**	0.09	0.33
			T1	0.02	A2	0.46	**0.91**	**1.00**
			T2	0.39	Fz	0.38	0.12	0.45

Table II shows the estimated stochastic relevance values for each EEG channel (DB1 data), computed by the SRA and STFT which is the combination that achieves the best classification results (see Table I). 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. Fig. 2 (upper) shows corresponding channels selected by spectral methods and stochastic relevance (SRA) with the visual inspection on the scalp topographic map at patient 1 in DB1 database. As seen, high values achieved by all methods 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 Wt, STFT and EMD methods. Note that the relevance measures for all methods successfully selects the channels with more seizure activity (T1, T3, and T5) showing the highest relevance values. All results show that the method provides a better medical interpretability about the location of the epileptic region.

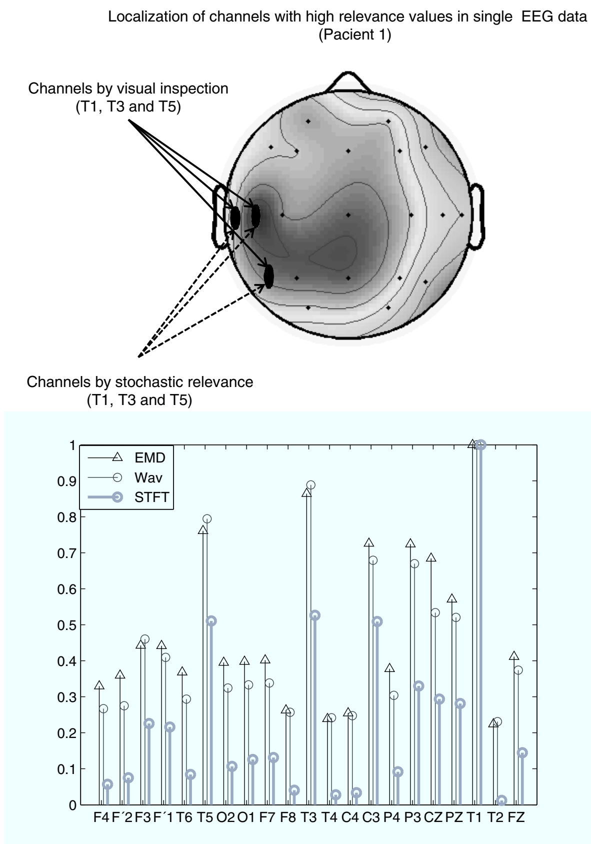

Fig. 2. Upper: Localization of the channels selected on scalp topographic map of STFT with SRA. Black areas represent a highest energy concentration than grey areas. Bottom: Relevance values obtained by spectral methods. Note that EEG channels with high stochastic relevance (bottom) correspond to those manually located on epileptogenic region (upper).

V. Conclusions and future work

A new method for relevance analysis in classification and channel selection for EEG multi-channel data with epilepsy is proposed. This method is based on Stochastic Relevance analysis of brain rhythms and has been tested with different spectral methods of the state of the art. Achieved results show that proposed method is a suitable alternative for classification of EEG segments and selecting EEG channels with seizure activity. The main advantage compared with other methods lies in its high performance in selecting epileptic channels, its adaptability for any spectral method, and its high accuracy with noisy EEG. The achieved results in channel selection, which are validated by experts through visual inspection and the scalp topographic map, show that SRA really provides an adequate approximation for epileptic channel localization, offering to medical environment an alternative to medical support in epileptic region localization. For the considered SRA as relevance measure, future work includes: comparing our approach with others relevance analysis 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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