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Analysis of the Automatic Detection of Critical Epochs from coma-EEG by Dominant Components and Features Extraction

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***Abstract*— Recent works showed that meaningful dominant components can be extracted from the EEG of patients in coma through an algorithm based on the joint use of Principal Component Analysis (PCA) and Independent Component Analysis (ICA). A procedure for automatic critical epoch detection would support the doctor in the long time monitoring of the patients, thus we investigated the automatic quantification of the criticality of the epochs. In this paper we propose a procedure based on the extraction of dominant components and features for the quantification of the critical state of each epoch, in particular we use entropy and kurtosis. This feature analysis allowed us to detect some epochs that are likely to be critical and that are worth being carefully inspected electrographically by the expert.**

I. Introduction

Recent works showed that meaningful dominant components (DCs) can be extracted from the EEG of patients in coma through the joint use of Principal Component Analysis (PCA) and Independent Component Analysis (ICA) [1]. In this paper we propose a procedure based on the extraction of dominant components and features for the quantification of the critical state of the epochs (non-overlapping data segments). We consider *critical* an epoch if the EEG activity during that epoch is higher than the rest of epochs.

The EEG is a technique that measures the electric field produced by the bioelectric impressed current density, associated with neuronal activity, through a set of scalp electrodes properly placed over the head. The visual inspection of the EEG is worldwide accepted as a key step in the cerebral death assessment of patients in coma, because the EEG is linked to the electric activity of the brain [2], [3], [4]. The bioelectric pattern of the patient in coma is monitored for a long time in order to detect any tiny electrical activity of the brain. In case no cerebral electrical spontaneous activity is observed, the patient is thought to be dead.

Since the time duration of the coma EEG may be very long, it is worth to investigate the possibility of automatic detection of the critical epochs in order to support the doctor in the long time monitoring. Thus we are headed to study the automatic detection of critical epochs.

Assessing the cerebral death may be troublesome because of the artifacts: artifacts are signals not related to the cognitive activity, they may be generated by external factors (electrical line noise, interference) or by non-cognitive inner factors (muscle activity, eye blinking, eye movements). The artifacts are superimposed to the useful signals we aim to analyze and it stand to reason that they are very unwelcome, especially if the useful signals are weak, such as the EEG of patients in coma. Moreover, the intensive care environment, that is the typical recording environment for coma-EEG, is full of many electromedical working equipments [5], [6], thus the external artifacts are very likely to occur.

An automatic critical epoch detection procedure should label the epochs that are worth being inspected particularly carefully by the expert, so that he can figure out whether the detected activity is related to artifacts or to brain activity.

Recent works showed that meaningful dominant components (DCs) extracted from coma-EEG included almost the entire information content of the raw signals [1]. The extraction of the DCs is a two step procedure: the first step is PCA and the information content of a certain principal component is estimated calculating the ratio between its eigenvalue and the sum of all the eigenvalues (more details are provided in [1]). Another recent work [7] showed the ability of kurtosis and entropy, Renyi's entropy in particular, to quantify the criticality of artifactual epochs in EEG. In this paper we analyzed the characteristics of the critical epochs and we introduced kurtosis and entropy as markers for the detection of criticality. For this purpose EEG data recorded in an intensive care environment were analyzed. The paper is organized as follows: the second section explains how the dominant components are extracted from the EEG, the third section explains why we propose the entropy and the kurtosis as markers for the critical epoch detection, the fourth section reports the results and the last section reports the conclusions.

II. Methodology

A. The extraction of the dominant components

In this section we describe the method for the extraction of the dominant components. Given an epoch of the recording, PCA extracts the principal components (PCs) and then the PCs are projected into a lower dimension embedding space so that we lose at most 20% of the information in the raw data. Previous work showed that we can completely embed an 1-sec epoch of coma-EEG in a 2$\sim$3 dimensional space [1]. ICA is then carried out in order to extract the independent components from this new dataset and the most meaningful component is selected as dominant component according to

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the variance. This algorithm can embed the information of a coma-EEG epoch in a few dominant components, due to the tiny information content of the EEG, thus the epoch can be completely descripted by them [8].

First of all we divided the dataset in 1sec non-overlapping segments (epochs) and we extracted the dominant components from each epoch.

PCA is a classic technique that, given a set of multidimensional observed variables, yields a set of uncorrelated variables that are ordered by reducing variance. The uncorrelated variables are linear combinations of the original variables and the last variables of this set can be removed with minimum loss of the information carried by the original data [9]. PCA is commonly used to reduce the dimensionality of a data set while retaining as much information as possible.

ICA is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals. ICA defines a generative model for the observed multivariate data, which is typically given as a large database of samples. In the model, the data variables are assumed to be linear mixtures of some unknown latent variables, and the mixing system is also unknown. The latent variables are assumed nongaussian and mutually independent, and they are called *independent components* (ICs) of the observed data. These independent components, also called sources or factors, can be extracted by ICA [9]. Many algorithms for ICA have been proposed in the last years. We exploited the extended version of the Bell-Sejnowski INFOMAX algorithm [10], [11].

B. Feature extraction

Our goal is to explore the automatic detection of the critical epochs, in other words the epochs that are worth being inspected particularly carefully. When a patient is in coma, it is hoped to detect any activity that is small or even tiny. The amplitude of the EEG of these patients is very tiny, the typical brain waves are not visible thus, in case of restart of the brain activity, the epoch is supposed to have particular statistical characteristics compared to the rest of the epochs. A critical epoch will be odd because an unexpected event occurs, it will be less random with respect to the epochs in which a continuous background activity is observed. Any activity is hopeful to be detected, even some artifacts, for example the ocular or muscular artifacts. These artifacts are characterized by a peaky distribution and could be detected by a measure of peakyness. The parameters that are able to estimate the randomness and the peakyness are the entropy and the kurtosis, respectively. They were proposed for the detection of the artifacts in normal EEG [12], we propose to use them for the detection of brain activity in coma EEG. In particular we propose to use the Renyi's definition of entropy. Since the dominant components include most of the information content of the epochs, in order to extract the features of each epoch we processed the corresponding dominant component.

The Renyi's entropy and the kurtosis were computed for each dominant component (i.e. epoch), they were normalized to zero-mean, unit-variance and amplitude in the range -1 to 1. If at a least one of the two features of a certain component exceed the fixed threshold (0.6 for kurtosis and -0.6 for entropy), the component was marked and the corresponding epoch was thought to be critical.

Further investigation will be devoted to the optimization of this threshold setting.

1) Kurtosis: Given a scalar random variable x, kurtosis has the following expression:

$$k = m_4 - 3m_2^2 \tag{1}$$

$$m_n = E\{(x - m_1)^n\} \tag{2}$$

where m_n is the n-order central moment of the variable and m_1 is the mean. Kurtosis is positive for peaked activity distributions, typical of eye blink, cardiac artifacts and muscular artifacts; kurtosis is negative for flat activity distributions, typical of noise [12].

2) Renyi's Entropy: As a measure of randomness of the epoch, we used the Renyi's definition of entropy. For a random variable y, whose pdf is $f_Y(y)$, the Renyi's entropy is defined as:

$$H_{R_\alpha}(y) = \frac{1}{1-\alpha} \log \int_{-\infty}^{+\infty} f_Y^\alpha(y) dy \tag{3}$$

$$H_{R_\alpha}(y) = \frac{1}{1-\alpha} \log\{\frac{1}{N^\alpha} \sum_j [\sum_i k_\sigma(y - y_i)]^{\alpha-1}\} \tag{4}$$

where α is the order of the entropy and the expression (4) results from the application of the kernel estimators and Parzen windowing [13], in fact y_i is the ith sample of a *N* samples Parzen window sliding over the signal. If the random variable is concentrated in small temporal intervals (i.e. an unexpected event), their probability densities take large values in a certain interval and give a strong contribution to the integral in the (3), thus the entropy is small, because $\alpha \geq 1$. This feature of the entropy help us to mark the signals that are concentrated in small temporal intervals with high probabilities and, therefore, which are very likely to account for a restart of the brain activity or artifacts.

The order of the entropy was set at 2, in order to equally emphasize the sub-gaussian and the super-gaussian components [13].

III. Results

A. EEG data description

The EEG was recorded in an intensive care environment. The data were acquired through 19 electrodes placed on the scalp according to the international standard 10-20 by Jasper (the electrode montage and the EEG are shown in Figure 1), we chose a monopolar montage, with the reference electrode placed in a neutral point of the scalp. The sampling rate was set at 256 Hz and the time duration of the recording is 51 sec. The toolbox EEGLAB [14] was exploited to plot the EEG signals, to run PCA and ICA and to plot the 2-D maps.

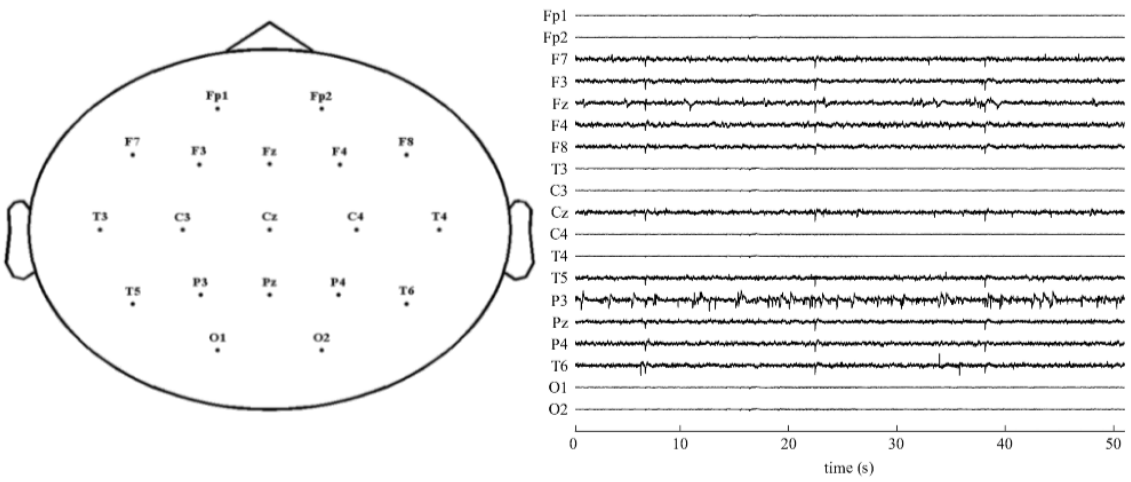

Fig. 1. The electrode montage and a 50sec EEG segment from a patient in coma.

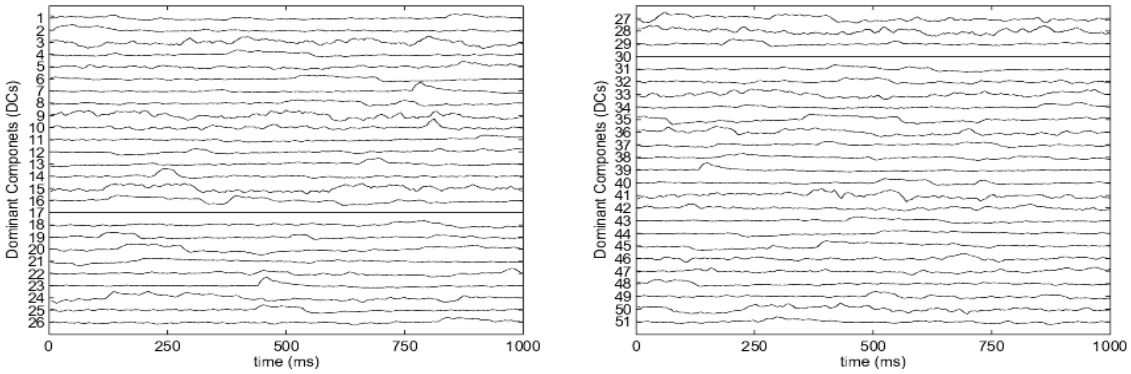

Fig. 2. The dominant components: each one of the 51 epochs is represented by its dominant component.

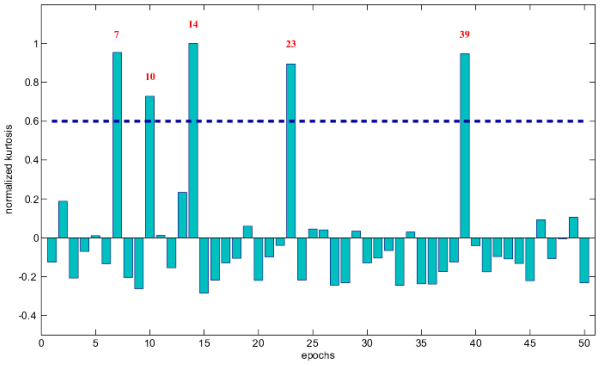

Fig. 3. The normalized kurtosis of the epochs. The kurtosis exceeds the threshold 0.6 for the epochs EP7, EP10, EP14, EP23, EP39.

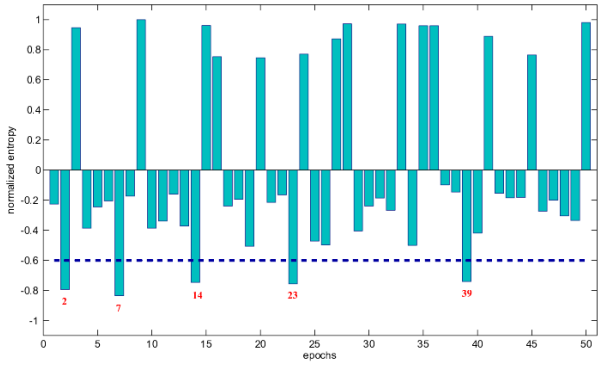

Fig. 4. The normalized Renyi's entropy of the epochs. The entropy exceeds the threshold -0.6 for the epochs EP2, EP7, EP14, EP23, EP39.

B. Dominant components extraction

The EEG recording was first divided into 1-sec epochs, so that we had 51 epochs, then the DCs were extracted as explained in II-A. For each epoch PCA was applied and then the information content of each component was estimated. Once we checked that we could embed our data in lower-dimensional space, we discarded the less meaningful components and we passed this new dataset through ICA. We selected the most meaningful component (the dominant component) from the set of ICs. Figure 2 shows the dominant components extracted from the epochs.

C. Feature Extraction

The kurtosis was estimated according to the equations in Section II-B.1. The results are plotted in Figure 3: the critical epochs (EPs) are EP7, EP10, EP14, EP23, EP39. The Renyi's entropy was computed according to the equations in II-B.2 and the results are plotted in Figure 4: the critical epochs (EPs) are EP2, EP7, EP10, EP14, EP23, EP39.
It is worth pointing out that the epochs EP7, EP14, EP23, EP39 are critical according to both the measures. The dominant components associated to the epochs EP7, EP23 and EP39 are shown in Figure 5 whereas the dominant components associated to the epochs EP2, EP10 and EP14 are shown in Figure 6. These are the epochs which are worth being inspected with particular care in order to figure out whether the detected waves are associated to brain activity or to artifacts. The critical time point of each epoch is highlighted with a red vertical dashed line. Looking at the mapping of the EEG at the critical time points (Figures 5 and 6), we realized that there are two kind of critical behaviour of the EEG signals: the first one is characterized by a relative high amplitude in the frontal and occipital region and a low amplitude in the central, fronto-temporal and parietal regions. The second kind of behaviour is characterized by a concentration of the activity in the electrode P3.

IV. Conclusions

This paper proposed a method for the evaluation of the criticality of epochs in coma-EEG. The technique is based on the joint use of PCA and ICA for the dominant component extraction, and on higher order statistics (kurtosis and entropy) for the extraction of features from the dominant components. The EEG recording was divided into non-overlapping epochs and then each epoch was processed. Once the features were extracted, the epochs that were likely to be critical according to a threshold were selected. This feature extraction detected some epochs that are worth being inspected particularly carefully by the expert. Further investigation will be devoted to the optimization of the statistics and of the thresholds settings.

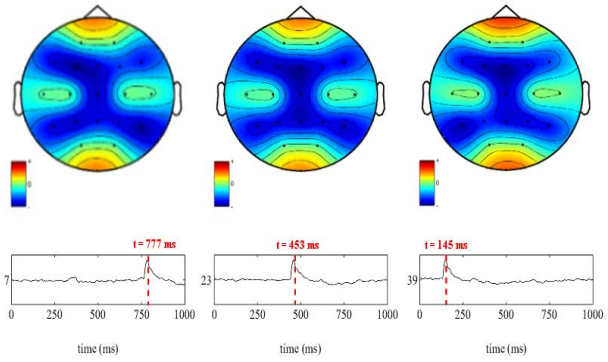

Fig. 5. The dominant components DC7, DC23, DC39 and the mapping of the critical epochs. The dominant components are plotted in the bottom, the critical time point of each epoch is highlighted with a red vertical dashed line. The EEG mapping at the critical time points is shown on top.

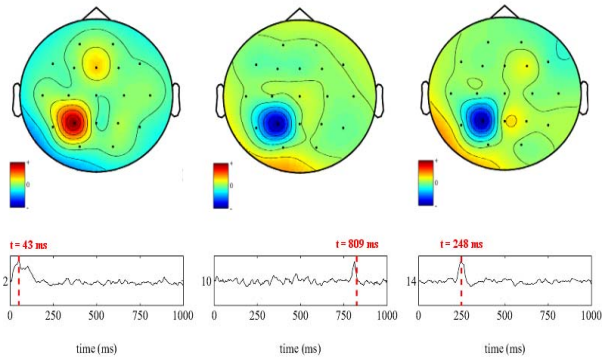

Fig. 6. The dominant components DC2, DC10, DC14 and the mapping of the critical epochs. The dominant components are plotted in the bottom, the critical time point of each epoch is highlighted with a red vertical dashed line. The EEG mapping at the critical time points is shown on top.

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