EEG WINDOWED STATISTICAL WAVELET DEVIATION FOR ESTIMATION OF MUSCULAR ARTIFACTS

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ABSTRACT

Electroencephalographic (EEG) recordings are, most of the times, corrupted by spurious artifacts, which should be rejected or cleaned by the practitioner. As human scalp EEG screening is error-prone, automatic artifact detection is an issue of capital importance, to ensure objective and reliable results. In this paper we propose a new approach for discrimination of muscular activity in the human scalp quantitative EEG (QEEG), based on the time-frequency shape analysis. The impact of the muscular activity on the EEG can be evaluated from this methodology. We present an application of this scoring as a preprocessing step for EEG signal analysis, in order to evaluate the amount of muscular activity for two set of EEG recordings for dementia patients with early stage of Alzheimer's disease and control age-matched subjects.

Index Terms— Electroencephalography, Electromyography, Wavelet transforms, Biomedical signal processing

1. INTRODUCTION

Artifacts in the EEG can be defined as any difference of potential produced by an extra-cerebral source [1]. In addition to electrical pulse noise and movement artifacts, ocular, electromyographic (EMG), electrodermal, electrovascular and respiratory signals can interfere with the EEG. EMG artifacts are quite difficult to recognize and discriminate because they may display similar patterns as usual EEG brain signals, in the same frequency range [2]. EEG analysis may be therefore strongly impaired by the presence of such muscular artifacts. The importance of artifact detection, either in order to reject them or remove them, has been already emphasized in the scientific literature. However, manual human artifact rejection can be biased and not reliable for scientific investigations. For instance, epoch by epoch agreement in sleep stage assignment of artifact scoring between 5 experienced sleep technologists from different laboratories reported poor consistency [3]: mean epoch by epoch agreement between scorers was rather low, globally 73%, and depended on the laboratory the technologist worked in. Therefore, automatic methods are preferable to manual rejection.

The well known approaches for automatic detection of artifacts are usually based on threshold methods for EEG potentials or power spectrums [4], regression based models [5], or projection based methods [6]. Recently, Independent component analysis (ICA) has been successfully applied to reduce some selected artifacts by exploiting statistical independency criterions [8],[7]. Using ICA semi-automatic criterion was proposed [9] for rejection of some artifacts. However, despite of promising results, ICA approach still needs manual identification and sorting components corresponding to specific artifacts, so to obtain a reliable result, human still need make intervention to optimally process the data.

Instead of exploiting raw EEG signal in the time or the frequency domain, we exploit wavelet joint time-frequency representations (TFR). Such TFR were proven to be useful for EEG ocular artifacts denoising [10]. Moreover, using an appropriate normalization, the so-called 'z-score', wavelet time-frequency maps precision can be enhanced for artifact detection [11]. However, up to now, precise time-frequency properties of muscular artifact shapes has not been fully explored. We propose here a novel approach, based on the time-frequency shapes specificity of artifacts, in order to asses automatically the degree of EMG corruption of EEG signals.

In order to confirm usefulness and validity of our approach we have designed special experiments: During EEG recordings, muscular artifacts were voluntarily provoked (intentional) and controlled. Our purpose is discriminate and to score these artifacts, while exploiting only raw EEG signals. The new approach is developed for a large panel of muscular artifacts, ranging from eye artifacts to head, jaw or body movements. The method exploits time-frequency characteristics of EEG signals to define optimal time length of the epochs of analysis. Our approach is designed for situations where different groups of signals are to be compared; the method returns a score for each signal, representing the quantitative level of EMG activity. We then try to obtain the same quality of signals in each group (the same amount of artifacts).

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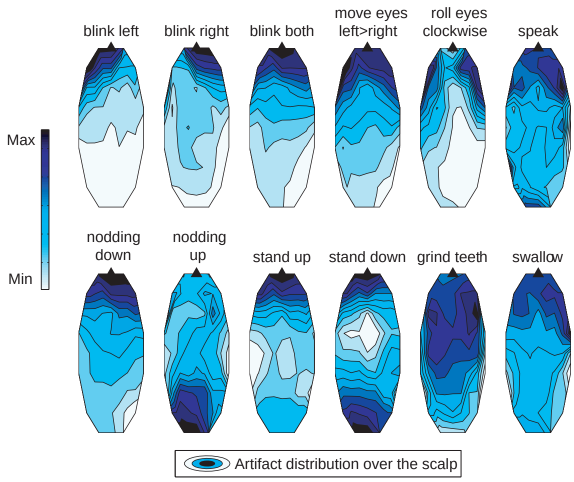

Fig. 1. Distribution of power for various QEEG intentional (controlled) artifacts after z-score normalization compared to baseline. The white color zones represents electrode locations where the activity (bandpass filtered in the range 10-120 Hz) are close to baseline activity and dark blue color denotes zones in which we observed increasing power.

2. DATA

EEG signals corrupted by EMG, were acquired using a 64 channels EEG Biosemi system (sampling frequency rate 1KHz), with active electrodes. The subjects were asked (with control) to produce voluntarily, one by one, muscular artifacts ($n = 10$ trials for each artifact). Ten different muscular artifacts were produced: eye blinks (left $n = 10$ trials, right $n = 10$, both $n = 10$); eye movements (look from left to right $n = 10$), roll eyes (clockwise n=10); speaking (speak 'kampai' $n = 10$); swallow some water ($n = 10$); move head ($n = 10$); nodding first down then up ($n = 10$); grind teeth on chewing-gum ($n = 10$) three times; stand up (30% of full standing) and sit down again ($n = 10$) (see Fig.1). The database consisted of 100 recordings (10 trials for each 10 artifacts).

In the course of another clinical study, EEG recordings (Deltamed EEG machine) from elderly patients affected by Alzheimer's disease and followed clinically (labeled AD set) and from age matched controls (labeled Control set) were recorded, with electrodes located on 19 sites according to the 10-20 international system. Reference electrodes were placed between Fz and Cz, and between Cz and Pz. Sampling frequency rate was 256 Hz, with bandpass filter 0.17-100 Hz. When possible, periods of 2.5 seconds were selected in a 'rest eyes-closed' condition for each patients. Two data sets, Control set (n=39), and AD set (n=33) are to be analyzed.

3. METHOD

3.1. WAVELET TIME-FREQUENCY TRANSFORMATION

Wavelets, especially complex Morlet wavelets [12] have already been widely used for time-frequency analysis of electroencephalographic signals [13], [14], [15]). Complex Morlet wavelets $w(t)$ of Gaussian shape in time (deviation σ) are defined as:

$$w(t) = A.e^{\frac{-t^2}{2\sigma^2}}.e^{2i\pi ft} \qquad (1)$$

where σ and f are interdependent parameters, A is a normalisation factor equal to $(\sigma\sqrt{\pi})^{1/2}$, with the constraint $2\pi ft > 5$; the wavelet family defined by $2\pi ft = 7$ was chosen, as described in [13]. For each time sample t, and each frequency bin f, wavelet transform computes one coefficient c_{ft} (continuous transform was approximated with 1 Hz steps in frequency). Wavelet representations can be investigated in regard to a baseline activity. To this end, a usual method is to normalize the time-frequency representation depending on the mean μ_f and standard deviation σ_f of each frequency bin f in the baseline activity (the so-called z-score [11]). In order to detect artifact corrupted activity, the baseline activity should be representative of non noisy signals. However, EEG signals generally present a low signal-to-noise ratio, the most reliable method is therefore to repeat the estimation of μ_f and σ_f on several clean signals ($>$ 30 signals - here we used 50 signals with the lowest possible apparent noisy activity), and finally to compute the following normalized score:

$$z_{ft} = \frac{c_{ft} - M_f}{S_t}, \quad \forall t, \qquad (2)$$

where M_f is the average of each b baseline's mean $\mu_f(b)$ for frequency f:

$$M_f = \overline{\mu_f(b)} \qquad (3)$$

and S_f is the average of each b baseline's standard deviation $\sigma_f(b)$ for frequency f:

$$S_f = \overline{\sigma_f(b)} \qquad (4)$$

Each artifact has specific time-frequency shapes, with sharp activity in the high frequency range (see Fig.2 (a) and Fig 2 (b)). As a comparison, EEG oscillations are less sharp in high frequencies and have higher amplitudes in low frequencies, with usually well defined time duration (more than 3 time periods [15]) (see Fig.2 (c)). The time-frequency joint representation allows to extract these characteristics, by defining time-frequency windows of interest which will be more precise than the usual time-windows used to define epochs for the artifact scoring.

3.2. WINDOWED Z-SCORE

We define two bands of interest in the frequency range: $\alpha+\beta$ [10-35] Hz and γ [60-90] Hz frequency ranges (F_1=26 frequency bins and F_2=31). For these two bands of interest,

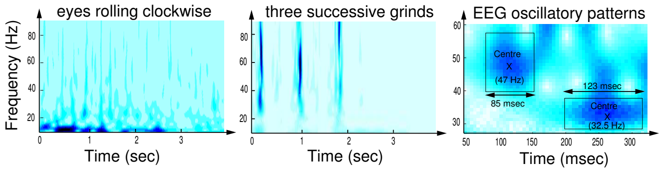

Fig. 2. Sample of wavelets time-frequency profiles for artifacts: (a) controlled eyes rolling clockwise, (b) teeth grinding three times compared to (c) typical clean EEG oscillatory patterns .

we define shifting time-frequency windows of 4 time periods around the central frequency (time length T_1=180 milliseconds for $\alpha + \beta$ and T_2=53 milliseconds for γ). Using these windows, shifted along the time axis, the scores are computed for 5 electrodes positions $E = [F_{p1}, F_{p2}, T_7, T_8, O_z]$; these peripherally distributed electrodes are good references for EMG activity (see e.g. fig.1: central electrodes, located above aponeurosis, are less likely to record EMG activity).

In order to assess this general impact, we combine information of low and high frequencies and define a deviation score W_s (which indicates the level of noise within the signal) :

$$W_s = \max_e(L_s(e), H_s(e)), \tag{5}$$

where e represents EEG electrodes in E, L_s and H_s are the scores for the signal in $\alpha + \beta$ and γ frequency ranges:

$$L_s(e) = \langle\sigma_{\alpha+\beta}(\tau)\rangle_\tau = \langle\sum_{f=10}^{35}\sum_{t=\tau}^{\tau+T_1}\frac{(z_{ft} - \overline{z_{ft}})^2}{F_1T_1 - 1}\rangle_\tau \tag{6}$$

and

$$H_s(e) = \langle\sigma_{\gamma}(\tau)\rangle_\tau = \langle\sum_{f=60}^{90}\sum_{t=\tau}^{\tau+T_2}\frac{(z_{ft} - \overline{z_{ft}})^2}{F_2T_2 - 1}\rangle_\tau \tag{7}$$

Where $\overline{z_{ft}}$ denotes the average z_{ft} in the time-frequency window. The deviation score W_s evaluates for the quantitative proportion of artifacts in the signal, and is based on standard deviation rather than usual measures of amplitude: Evoked EEG activity can display high amplitude activity, but are unlikely to have sharp peaks, therefore standard deviation is a more specific measure (power measures are too conservative and tend to detect evoked potentials as artifacts [16]).

3.3. ARTIFACT SCORING

Instead of rejecting all artifacts, we are here interested in evaluating a 'signal-to-artifact' ratio. For instance, eye blinks can not be rejected for a long time duration in 'eyes opened' condition, and also will not elicit the same degree of perturbation within the EEG signals as compared to body movements. In other words, we are interested in a quantitative rather than qualitative approach.

Table 1. Quantitative evaluation of perturbations of the EEG signals due to artifacts, using W_s *log* average scoring (rounded to obtain the perturbation order). Application to preprocessing of EEG from Alzheimer and Control patients (mean and standard deviation of W_s are reported).

Artifact type	$log_{10}\langle W_s\rangle$	Order
Eye blink	0.24	0
Eye move	0.88	1
Speaking	1.29	1
Swallow	2.13	2
Grind 3 times	2.84	3
Nodding	2.95	3
Standup	3.27	3
AD set	0.27±0.39	0
Control	0.15±0.17	0
Clean AD	0.15±0.17	0

Table 1 reports the average $\log W_s$ score for each type of artifacts (averaged on 10 trials, except for eye blinks grouped in 30 trials and eye moves grouped in 20 trials). The score estimate the impact of specific artifact on EEG (strong impact elicits strong score), and were computed for 2.5 sec time windows during and after the artifact was triggered. Using this score, one can discard signals depending on the desired quantitative amount of artifacts accepted (for instance, for experiments with eyes opened conditions one may accept artifacts of order up to 1).

We have used this method to evaluate the distribution of EMG power in the two groups of patients (AD set, Control Set). The purpose of this application is to produce two databases with an equivalent amount of EMG noise, so that noise would not bias the study. The distributions differed, AD set W_s values are above Control set values (Kolmogorov-Smirnoff signed test for difference of distributions p = 0.04), which means that the AD set contains significantly more EMG. Generally, low score for artifacts are found in each of the sets (on the order of 0). After removing the 6 most noisy signals for AD set(in the table: Clean AD), the distributions becomes similar (equal mean, equal standard deviation, and Kolmogorov-Smirnov test p $\gg$ 0.10), which fulfills our preprocessing objective.

4. CONCLUSION AND DISCUSSION

We presented a novel approach for artifact evaluation and rejection, based on the time-frequency properties of sharpness in high frequencies and in low frequencies. The evaluation score of the W_s represents the overall impact of muscular artifact onto EEG signals. Our approach provides consistent results for intentionally generated and controlled artifacts.

The deviation scores W_s were computed for 2.5 seconds epochs, with optimal sliding time-frequency subwindows. A shorter epoch can also be considered, however as some artifacts elicit long duration activities in low frequency range the score can become less reliable for slow muscular artifacts (typically, eye movements, or body movements). On the other hand, epochs longer than 2.5 seconds could be less sensitive to fast transient artifacts (such as eye blinks).

In our experiments we used two frontal, two temporal and one occipital electrodes. The method could be extended to other sets of electrodes, and more electrodes could be applied. However, the computational demand of such an investigation would become heavy. As the results obtained with this limited set of electrodes are satisfactory, we think that the number of electrodes used is sufficient.

This method is well suited for muscular artifact estimation. However, one should take into account that the effect of other types of artifacts - i.e., electrodermal, electrovascular and respiratory artifacts - has not yet been evaluated. Furthermore, epileptic activity may also displays sharp waves, and therefore, could be detected as muscular artifacts by this method.

The proposed score W_s is potentially useful when several sets (in our example 2 sets) of signals are to be analyzed and compared regarding some feature and markers. In such case it is necessary to assess and compare EMG noise level. This step of evaluation EMG noise should be always led before EEG signal comparisons (for instance for medical abnormal EEG detection). It could also be combined with ICA for EMG related independent component removal, following wavelet ICA the method suggested in [17]. In a final step, we may asses automatically the amount of EMG noise remaining after ICA cleaning of EEG signals in such a way that (W_s should decrease to a satisfactory level).

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