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Detection and Removal of Ocular Artifacts from EEG signals for an Automated REM sleep analysis

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Abstract— **Rapid eye movements (REMs) are a prominent feature of REM sleep, and their distribution and time density over the night represent important physiological and clinical parameters. At the same time, REMs produce substantial distortions on the electroencephalographic (EEG) signals, which strongly affect the significance of normal REM sleep quantitative study. In this work a new procedure for a complete and automated analysis of REM sleep is proposed, which includes both a REMs detection algorithm and an ocular artifact removal system. The two steps, based respectively on Wavelet Transform and adaptive filtering, are fully integrated and their performance is evaluated using REM simulated signals. Thanks to the integration with the detection algorithm, the proposed artifact removal system shows an enhanced accuracy in the recovering of the true EEG signal, compared to a system based on the adaptive filtering only. Finally the artifact removal system is applied to physiological data and an estimation of the actual distortion induced by REMs on EEG signals is supplied.**

I. INTRODUCTION

REM sleep episodes, which occur cyclically during the night, are primarily identified by low voltage fast EEG activity, suppression of muscle tone and rapid eye movements (REMs). REMs are not uniformly distributed as they indicate the REM phasic phase which episodically interrupts the tonic one and is characterized by REMs bursts and muscle twitches. In young adults, REMs are present during 14-27% of REM sleep, often (60-70%) grouped in bursts. The particular organization of REMs during the night represents an important physiological feature with clinical implications [1].

Besides, REMs represent one of the main sources of contamination in sleep EEG recordings. Ocular movements, causing a rotation of the intrinsic electric dipole within the eyeball , produce oscillating electrical fields which corrupt, by propagation, the brain potentials over the whole scalp and make difficult the EEG quantitative interpretation[2,3]. However a precise quantification of EEG spectral power density during REM sleep would have relevant physiologic significance and could provide valuable information for understanding pathophysiological issues and assisting the diagnosis of some neurodegenerative diseases[4].

For these reasons, the aim of this work is the development of a fully-automated procedure for both REMs detection and corresponding EEG artifacts removal. The two goals have been obtained applying data-driven thresholds on the Wavelet-transformed electrooculograms (EOG) and replacing corrupted EEG segments with the values predicted by an adaptive filter, respectively. The stages of detection and correction were fully integrated since the adaptive-filter-based correction was performed only in correspondence of detected eye movements. The procedure enabled us to obtain actual estimates of spectral power distribution of REM brain activity, not corrupted by eye artifacts as we demonstrated by objectively evaluating the performances of both detection and correction stages by means of simulated phasic REM EEG and related EOG signals. Finally, the new tools were applied to real REM sleep recordings, in order to evaluate the actual distortion induced by REMs in EEG spectral analysis during sleep.

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II. PRELIMINARY ANALYSIS OF OCULAR ARTIFACTS

EOG and EEG signals were preliminarily recorded from four healthy subjects (24-35 years) instructed to perform eye movements in response to trigger sounds in four different main directions (vertical, horizontal, and oblique, circular), while the correspondent electric potentials were recorded using a HydroCel Geodesic Sensor Net (HCGSN) and Net Amps 300 (GES300), equipped with 128 electrodes uniformly distributed across the scalp. In line with findings of similarity between kinematic parameters of REMs and saccadic eye movements during wakefulness , subjects were lying on a bed, in the dark, with their eyes closed. They performed both single, temporally-isolated movements and burst of movements in order to reproduce the frequent REMs bursts. Data were collected with a sampling rate of 500 Hz, electrode impendence below 50 kΩ, resolution of 24 bit, precision of 70 nV/bit (0.07μV). The recording reference was set at the vertex electrode (Cz in the international 10/20 system). EEG raw data were offline re-referenced to the mastoid electrodes average potential in order to obtain monopolar-like potentials, while EOG vertical (VEOG) and horizontal (HEOG) signals were obtained as bipolar derivations. All data were 0.1-40 Hz band pass filtered. The precise time instants of stimuli was used as starting information to extract the signals segments directly associated to each eye movement. A preliminary analysis of these waveforms was carried out. Averaging over all EOG time sequences related to each type of movement, it was possible to extract a template of the typical ocular potentials derived from each of them. The visual inspection of such templates showed that the waveforms related to movements performed in close succession corresponded to the concatenation of single deflections without distortion, and movements in oblique and circular directions can be obtained as superposition of vertical and horizontal deflections. Thus, these positive or negative deflections in the HEOG or VEOG signals were assumed as elementary patterns to detect. Furthermore, in order to obtain an impression of the spectral pattern of the ocular artifacts, the main spectra of EEG and EOG time sequences were evaluated (periodogram calculated as mean Hamming windowed FFT) and compared with the ones derived from corresponding sequences in which the same subjects maintained fixed the gaze. The logarithm of their ratio was computed and it revealed that the ocular artifact contribution was mainly concentrated at low frequencies, below 10-15 Hz, rapidly decreasing with the increasing of frequency for both EOG and EEG derivations. The experimental EOG recordings obtained in this phase of the work, directly associated to voluntary eye movements similar to REMs, were also used in the following phases of construction of the REMs detection algorithm and validation of the total system respectively for setting the algorithm thresholds and creating the simulated signals.

III. REMs DETECTION METHOD

The REMs detection method was based on Wavelet Transform. In particular the sum of coefficients in the range of scales from 100 to 600 (corresponding to the frequency band 0.8-5 Hz) was individuated as the most discriminatory variable between movement-holding and movement-free EOG segments. Different wavelet waveforms were tested, but the Haar function appeared as the most convenient one, effectively marking with consecutive peaks each elementary movement time period, and providing further information about the versus of the movement. However, during REM sleep we also had to cope with the presence in EOG recordings of other oscillations in the same frequency band of those deriving from eye movements, which are mainly related to the propagation of theta EEG activity and to other artifacts, and cause pronounced spurious peaks in the sum of wavelet coefficients. In order to extract the pairs of peaks associated to eye movements only, the detection algorithm evaluated magnitude, time distance, and other features of each pair of peaks in the EOG recording and selected only the pairs showing values compatible with those estimated for eye movements. A set of thresholds were consequently introduced in the algorithm, which has been derived accurately so as to maximize the capacity of the system to discriminate ocular peaks from the spurious ones, experimentally observing their features. In particular, a representative sample of ocular peaks was obtained applying the Wavelet transform to the EOG time sequences associated to the elementary eye movements of two of the subjects observed, whereas the spurious peaks were derived from experimental EOG recordings, obtained during tonic REM sleep. This REMs detection algorithm was applied separately to both vertical and horizontal EOG derivations. In the case of concurrent REMs detection in the two EOG channels (overlap greater than 50%), the two time intervals were merged and a single movement was considered.

IV. REMOVAL OF OCULAR ARTIFACTS FROM EEG SIGNALS

To date, several different correction procedures have been proposed for the removing of eye artifacts from EEG signals, among which regression based methods and principal and independent component analysis (PCA/ICA) are the most emphasized approaches [5]. In particular, the method proposed in [6] based on adaptive filtering technique was selected, because it shows elevate performance in recovering true EEG signals and results more accurate than simple time-domain regression method, being able to deal with the possible non stationary relationship between the reference EOG and the EOG component in EEG signals. In the system, the vertical (VEOG) and horizontal (HEOG) EOG derivations are picked up as reference inputs by two FIR filters of length M, which attempt to estimate the EOG contribution to the EEG electrode considered, allowing the true EEG to be obtained. The system converges to the optimum solution thanks to an adaptive algorithm for updating the weights of the transversal filters, which minimizes the mean square value of the error signal $e(n)$, defined as the difference between the starting EEG signal and the filters outputs. The adaptive algorithm chosen was the Recursive Least Squares (RLS) estimation, because of its superior stability and fast convergence. The cost function to be minimized in this method approximates the expected value of $e(n)$ by a weighted sample mean:

$$\varepsilon(n) = \sum_{i=M}^{n} \lambda^{n-i} e^2(i) \ , \qquad (1)$$

where λ is referred as forgetting factor and is $0 < \lambda \le 1$. The use of λ is intended to ensure that data in the distant past are forgotten and to afford the system the possibility of facing a non stationary environment. The principal drawback of such adaptive procedure lies in its incapacity of taking into account the bidirectional contamination existing between EOG and EEG signals, which could cause the removal of interesting cerebral activity also. In order to improve the accuracy in recovering the true EEG signal and to limit the distortion induced on it, in the current work, it was proposed, to activate the adaptive filtering system only in correspondence to the occurrence of REMs and to maintain it deactivated during the remaining sleep periods. In this way, it was possible to minimize the undesired removal of cortical activity, rendering the method more specific to REM sleep analysis. This was realized, using the information supplied by the detection algorithm to opportunely include or exclude the adaptive filtering system from the EEG signal processing scheme.

V. GENERATING ARTIFICIAL REM SIGNALS

Since the true EEG and EOG waveforms are not available in normal physiological studies, simulated REM EEG and EOG signals were created, which have allowed an actual validation of both detection and artifact removal procedure. In order to simulate the cerebral component of the signals, some EOG and EEG segments of tonic REM sleep recordings were selected, where ocular movements seemed totally absent at visual inspection. Instead, the ocular component of the EOG signal was created randomly superimposing to the cerebral component the EOG time sequences directly associated to eye movements extracted during the preliminary analysis. The time distance between two consecutive ocular events was determined step by step, sampling a random variable with a Poisson's distribution. To make the simulation specific for REM sleep, the parameter of such probability distribution was calculated through a preliminary raw evaluation of the REMs time density, based on a magnitude threshold only, made on true sleep recordings. Each eye movement inserted in the simulation was randomly selected among every type of movements experimentally observed, both single or repeated in close succession. In order to estimate the ocular component also at EEG derivations, it was decided to model the potentials propagation merely with propagation coefficients, calculated by a time regression analysis on the EOG and EEG experimental recordings. This was considered as a reasonable approximation since volume conduction can be considered instantaneous below 1000 Hz, and ocular artifact contribution is mainly localized at low frequencies, where the gain of the true propagation function remains quite constant over frequency.

VI. Validation of the Detection Algorithm

Since the exact instant in which each elementary eye movement was inserted in the simulation was known, it was possible to evaluate the effectiveness of the REMs detection algorithm only. Obviously, the EOG time sequences to be detected in this phase belonged to the two subjects who had not been considered and whose sequences hadn't already been used for the determination of the detection algorithm thresholds. The performance of the detection algorithm was described in terms of the percentages of correct (P_c), missed (P_m) and wrong (P_w) detections, which are reported below. P_c and P_m were evaluated respectively as the ratio of the number of detected and missed movements to the total number of elementary eye movements, whereas P_w represents the number of wrong detections over the total number of detections. The values obtained for the considered performance indexes are excellent, considering the small amplitude of the eye movements to be detected.

TABLE I. Effectiveness of the Detection Algorithm

P_c	P_m	P_w
94.78%	5.22%	1.8%

VII. Validation of the Ocular Artifact Removal Procedure

Applying the artifacts removal procedure to the simulated signals, the cleaned EEG signal obtained could be compared directly to the true EEG signal to be recovered. As it is shown in "Fig. 1", the removal system was able to activate the adaptive filtering exactly in correspondence of eye movements, producing a credible evaluation of the true signal when the ocular artifact was present, and completely not distorting it when the artifact was absent.

For a quantitative analysis, two parameters were considered, defined below, which describe the accuracy in recovering the true EEG signal respectively in the time and frequency domain: *MSE* ("Mean Square Error") and *MAE*("Mean absolute error").

$$MSE = \sum_{n=1}^{N} [e(n) - x(n)]^2 / N , \qquad (2)$$

where *e(n)* represents the EEG signal recovered by the artifacts removal procedure, while *x(n)* represents the true EEG signal. A global *MSE* value (MSE_t) was obtained considering the whole simulated signals. Moreover, the *MSE* was evaluated separately in the intervals of the EEG simulated signals where the ocular artifact was present (MSE_a) or absent (MSE_b), in order to estimate respectively the effectiveness of the removal system both in recovering and in not distorting the true EEG signal.

$$MAE = \sum_{n=1}^{N} [P_e(n) - P_x(n)] / (i - j) , \qquad (3)$$

where P_e and P_x are the power spectral density obtained respectively from *e(n)* and *x(n)*, while *i* and *j* define the frequency range considered. This parameter was in fact evaluate for five frequency bands: δ (0.5-4 Hz), θ (4-8 Hz), α (8-12 Hz), σ (12-16) and β (16-25 Hz). All the parameters listed above were then normalized, dividing them by the correspondent parameter obtained considering the recovered EEG signal equal to the simulated EEG, or, in other words, totally not cleaned up from ocular artifacts. Finally the parameters were averaged over the EEG channels analyzed. The registered mean *MSE* and *MAE* values revealed that the newly proposed removal procedure managed to a quite accurate reconstruction of the correspondent true EEG, both in the time and in the frequency domain. In particular, the following tables compare the values of the accuracy parameters (first rows) with those obtained using for the correction the system based on the adaptive filtering only (second rows).

TABLE II. Time Domain Accuracy

MSE_t	MSE_b	MSE_a
0.0122[a]	0.0002[a]	0.0631[a]
0.1159[b]	0.1018[b]	0.2114[b]

a. Values obtained with the new removal system.
b. Values obtained with adaptive filters only.

TABLE III. Frequency Domain Accuracy

MAE_δ	MAE_θ	MAE_α	MAE_σ	MAE_β
0.0096[a]	0.0098[a]	0.0114[a]	0.0122[a]	0.0123[a]
0.1506[b]	0.2241[b]	0.2514[b]	0.2926[b]	0.2941[b]

a. Values obtained with the new removal system.
b. Values obtained with adaptive filters only.

As expected, the *MSE* values calculated where the ocular artifact was absent strongly decreased, since the detection algorithm opportunely excluded the adaptive filter from the processing scheme. However also the mean MSE_a value showed a significant reduction. This results is probably caused by the fact that also when a eye movement is detected, the filter is gradually activated and its action remains limited until the ocular potential magnitude is greater than a fixed threshold. These two factor resulted in a significant improvement of the global time-domain accuracy of the system. Similarly also in the frequency domain the performance of the new system was enhanced, since the mean MAE values in all the five frequency band analyzed were an order of magnitude lower.

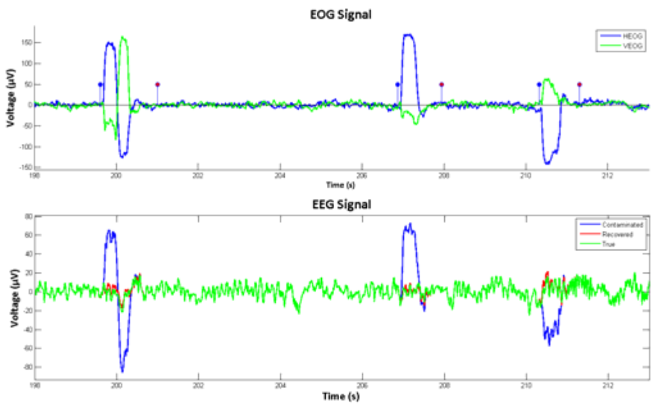

Figure 1. Top panel: EOG simulated signals with red and blue dots indicating beginning and end of each eye movement inserted. Bottom panel: EEG signal recovered (red trace) from the simulated signal(blue), compared to the one due to brain potentials only(green).

VIII. Application to Real Data

As last step of our work, the detection and artifact removal procedures were applied to real physiological data, recorded during the sleep of six healthy subjects. EEG and EOG data were collected with a sampling rate of 250 Hz, using a HydroCel Geodesic Sensor Net, equipped with 128 electrodes. After acquisition, the different sleep stages were scored through the visual inspection of each 30-second epoch, according to AASM'07, and the analysis was restricted to data segments associated to REM sleep. The spectral power distribution was evaluate, for each REMs sleep interval analyzed, both before and after the ocular artifacts removal.

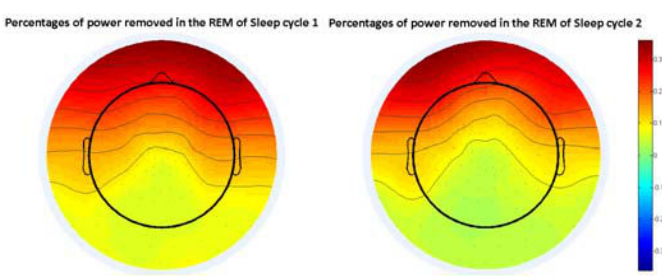

Figure 2. Percentages across the scalp of total power removed by the correction procedure, during the first two cycle of REM sleep (cycle 1 is reported on the left, and cycle 2 on the right).

Comparing the spectra obtained in these two conditions, it was possible to evaluate exactly how ocular artifacts can distort the true EEG spectrum within the frequency band of interest (0.1-25 Hz) and consequently affect the results of a normal REM sleep quantitative study."Fig. 2" shows the mean values obtained across the scalp for the percentage of removed power in the frequency band of interest. In greater detail, the same percentages were evaluated also in five more specific frequency ranges and were reported in the following tables.

TABLE IV. Percentages of Power Removed in Sleep Cycle 1

Channels	Frequency Band				
	δ	***θ***	***α***	***σ***	***β***
Frontal	0.19222	0.05291	0.03975	0.04145	0.04257
Occipital	0.06272	0.00355	0.00305	0.00481	0.00499

TABLE V. Percentages of Power Removed in Sleep Cycle 2

Channels	Frequency Band				
	δ	***θ***	***α***	***σ***	***β***
Frontal	0.17411	0.04850	0.03645	0.03429	0.04033
Occipital	0.04453	0.00358	0.00314	0.00435	0.00531

IX. Conclusion

The provided Detection and Removal REM artifacts procedure could become a valuable tool in both clinical and research activities, allowing a complete and automated analysis of REM sleep, both in terms of REMs time density and brain activity in the frequency domain. The proposed integration between the detection and the correction stages significantly improved the ability of the adaptive-filter-based removal system to recover the true EEG signal, limiting the distortion induced on it when no eye movement is present. Finally quantitative information about the actual distortion induced by REMs artifacts on brain activity spectrum was provided, which could help the interpretation of normal REM EEG quantitative studies.

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