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Derivation and modeling of two new features for the characterization of rapid and slow eye movements in electrooculographic sleep recordings

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ABSTRACT

This work presents a method for the derivation of two new features characterizing the occurrence of both, saccadic and slow eye movements (SEM), in electrooculographic (EOG) sleep recordings. Analysis of EOG activity is of fundamental importance for the clinical interpretation of a subject's sleep pattern. The features here presented are derived from purely horizontal EOG recordings, and have been built to be patient-adaptive and relatively robust against a variety of artifacts. Using the two derived features, performance analysis of two derived Bayes classifiers (respectively for the automatic detection of saccades and of SEM) was validated. Experiments were carried out using a database of 21 whole-night recordings. Automatic and human detections were obtained on a 30-s time grid. Two clinical experts were used as the standard reference. Average kappa indexes were obtained to characterize the agreement between this reference and the automatic detector. Automatic-reference and human–human REM agreements were 0.80 and 0.87, respectively, for the detection of saccades. Corresponding SEM agreements were 0.59 and 0.64, respectively. Our results closely match the expected inter-rater agreement and therefore support the robustness of the method and the validity of the implemented features for the automatic analysis of sleep EOG recordings.

1. Introduction

Analysis of the electrooculographic (EOG) activity is of fundamental importance for a good characterization of a subject's sleep pattern. The sleep process involves continuous physiological and behavioral changes, among them affecting the oculomotor activity, which persists even while sleeping, and shows distinctive relevant patterns throughout the different sleep stages [1,2]. Indeed, EOG activity is one of the mandatory biomarkers to be recorded during the course of polysomnographic (PSG) studies for the clinical diagnosis of sleep disorders [3].

EOG activity can be recorded using several methods, but in the context of the sleep studies the standard approach follows by placing pairs of electrodes attached to the skin surrounding the eye globe. The potential difference for each pair of electrodes can then be measured by taking into account the corneo-retinal standing potential existing between the front and the back of the human eye, which is altered as the eyes rotate [4].

Current standards for the evaluation of the sleep macrostructure classify sleep into four different stages (N1, N2, N3 and R) plus the wakefulness state or W [3]. Sleep stages N1-N3 integrate the so-called non-rapid eye movement (NREM) sleep, characterized by the absence of rapid eye movements (REMs) which are specifically associated to stage R [1]. More generally the term saccade is often used to refer to rapid eye movements (some bibliographic entries mention velocities ranging from 30 to 500 deg/s and durations from 30 to 80 ms [5]) with independence of whether these movements do occur during R or not. During W, for example, saccades result from the normal eye activity during wakefulness, even while resting awake, due for instance to reading movements, watching TV, or common eye blinking [3].

The so-called slow eye movements (SEM), on the other hand, are defined as rather sinusoidal slow waveforms with associated frequencies between 0.1–1 Hz, and are a typical phenomenon characterizing the wake-sleep transition. Specifically the American Association of Sleep Medicine (AASM) defines them as "conjugate, reasonably regular, sinusoidal eye movements with an initial

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deflection that usually lasts >500 ms" [3]. Usually the presence of SEMs increases linearly before the beginning of stage N1 (SEMs may be seen during eyes closed while still in W) and decreases progressively during the first minutes of N2 with the appearance of sleep spindles and K-complexes [6,7,3]. On the other hand, and even though for sleep scoring purposes SEMs are mostly associated with N1, some recent studies have also reported a significant presence of slow eye activity during R [8–10].

Visual analysis of the EOG activity is a routine task during the clinical scoring of PSG examinations. Visual scoring however is a tedious and very time-consuming task. Further drawbacks include the task to be influenced by the effects of both inter- and intra-scorer variability among diverse scorings (especially in the case of SEM [11,12]). As a result the costs associated to the analysis are high, and quality of the diagnosis may be compromised. With this perspective, the development of automatic detectors that help in the evaluation of the EOG activity is of obvious interest. Advantages of automatic detectors include as well the possibility to quantify and objectively measure this type of events, opening new possibilities both for clinical diagnosis and research. Indeed several works have been already published in the literature addressing this topic.

Regarding automatic REM detection, for example, already in the '70s–'80s several approaches can be found, mostly based on analogue filtering realizations, and on signal amplitude analysis [13,14–18]. Comparative analysis and critical review of some of these approaches can be found in [19,20,11]. More recently, Agarwal et al. [21] have presented a method using two EOG channels with the underlying rationale that REMs must occur in synchronization with the two channels, be phase-reversed, and satisfy a minimum amplitude criterion. For that purpose they preprocessed the two EOG channels to detect candidate REM events which are further characterized by extracting a set of features. Finally the candidate events are classified as REM, or discarded, by applying a set of derived decision rules. The proposal of Niemenlehto addresses the problematic of high false detections by developing an adaptive thresholding approach whose detection sensitivity is continuously adjusted throughout the analysis [22].

Most of the previous methods set detection thresholds based on different features associated to the velocity of the saccadic movements. Behrens et al. [23,24] argued that velocity-based approaches are limited by the fact that velocity values of the slow saccades overlap with the fastest SEM, and presented an algorithm for the detection of REMs based on the acceleration profile. In their work they also derived a subrogated feature namely postsaccadic amplitude energy that could be used as well for the detection SEM in the form of wake-sleep-wake transitions [24].

In contraposition to REM, the number of approaches dealing with automatic SEM detectors was initially rather scant, with first approaches dating back from the middle '90s [11,12] and the early 2000s [25,26]. According to the first validation experiments, automatic detection of SEM turned out to be a more complicated task, and indeed these first approaches showed in general lower reliability as compared to their contemporary methods for the detection of REMs [11,12].

In the last years, however, the number of developments for automatic SEM detection has increased. Virkkala et al. [27], for example, have developed an automatic detector of SEM for detecting unintentional sleep onset. Over the left and the right EOG channels referenced to the mastoid, they used the difference between the cross-correlation in the 1–6 Hz and in the 0.5–6 Hz bands as the major indicator of SEM. More recently Shin et al. have presented a real-time SEM detection algorithm based on feature-extracted parameters of the EOG, namely amplitude and mean velocity of the eye movement. Their aim was to prevent sleep-related driving accidents by detecting the sleep-onset as predictor of the driver's delayed-response [28].

The works of Magosso et al. [29,8] are based on the wavelet decomposition over bipolar EOG recordings acquired during overnight PSG studies. The choice of this technique was suggested "by the poor performance of filtering techniques in SEM detection", and because of the theoretical advantages that non-stationary techniques, such wavelet analysis, would provide for the detection of SEM. More recently Cona et al. [10] expanded the original method described in [29], including the capacity to individualize single SEMs (from previously detected SEM periods) and thus enabling computation of individual features for each wave. Validation of their algorithm, using individualized scorings of SEMs annotated by sleep experts, showed an improvement over the previous versions of the algorithm [10].

Nevertheless, and in spite of the number of applications for detection of saccades and SEM already available in the literature, current approaches still present a number of limitations. Some of the problems have to do with the limited performance of the current detectors, the excessive sensitivity to artifacts, the problematic to adapt to patient individual features, or the limited validation of the presented methods.

In this study we present a method for the derivation of two new features characterizing the occurrence, respectively, of rapid saccadic movements, and of SEMs. We propose the use of purely horizontal EOG recordings (between the outer canti of each eye) because other derivations introduce large EEG and movement artifacts. Several additional artifact rejection techniques are implemented, leading to the derivation of robust features which are tolerant to different sources of recording artifacts.

The added value of our method to the current state-of-the-art includes, in addition, that it is patient adaptive, avoiding the need of setting fixed detection thresholds. Instead detections are made proportional to a normalized and evolving baseline. Besides, both the saccade and the SEM features are calculated such that the magnitude of the scored events is measurable, thus allowing their quantification. The resulting features, on the other hand, are simple, given they are one-dimensional, and thus they can be easily plotted onto a screen synchronized with the raw EOG data. This allows the clinician a quick overview of the overall eye recording activity, which is a helpful resource for the analysis of the sleep stages. Finally, in contraposition to many of the previously referenced approaches, our validation is carried out using whole-night registrations, hence not limiting to subsamples or pre-selected intervals, nor excluding recordings from the validation due to technical reasons.

2. Methods

As introduced before, the method proposed here involves the processing of one EOG signal derivation for the extraction of two individual features characterizing the occurrence, respectively, of rapid saccadic movements and slow eye movement activity. Conceptually, the method consists of two main processing blocks: a first preprocessing of the raw EOG signal is carried out in order to perform signal conditioning, and to identify unreliable signal intervals; a second processing block works over the filtered EOG, and uses the reliability information in order to extract the aforementioned saccadic and SEM features.

2.1. Signal preprocessing

Before computation of the actual saccade and SEM features the raw EOG signal is preprocessed for artifact detection and for signal conditioning. Fig. 1 shows a schema of the preprocessing steps. Details over the functionality of the different modules are given in the subsequent sections.