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Technical note

An improved algorithm for the automatic detection and characterization of slow eye movements

Filippo Cona[a,*], Fabio Pizza[b,c], Federica Provini[b,c], Elisa Magosso[a]

[a] Department of Electrical, Electronic and Information Engineering "Guglielmo Marconi", University of Bologna, Via Venezia 52, 47521 Cesena, Italy
[b] Department of Biomedical and Neuromotor Sciences, University of Bologna, Via Ugo Foscolo 7, 40123 Bologna, Italy
[c] IRCCS Istituto delle Scienze Neurologiche, AUSL di Bologna, Bellaria Hospital, Via Altura 3, 40139 Bologna, Italy

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ABSTRACT

Slow eye movements (SEMs) are typical of drowsy wakefulness and light sleep. SEMs still lack of systematic physical characterization. We present a new algorithm, which substantially improves our previous one, for the automatic detection of SEMs from the electro-oculogram (EOG) and extraction of SEMs physical parameters. The algorithm utilizes discrete wavelet decomposition of the EOG to implement a Bayes classifier that identifies intervals of slow ocular activity; each slow activity interval is segmented into single SEMs via a template matching method. Parameters of amplitude, duration, velocity are automatically extracted from each detected SEM. The algorithm was trained and validated on sleep onsets and offsets of 20 EOG recordings visually inspected by an expert. Performances were assessed in terms of correctly identified slow activity epochs (sensitivity: 85.12%; specificity: 82.81%), correctly segmented single SEMs (89.08%), and time misalignment (0.49 s) between the automatically and visually identified SEMs. The algorithm proved reliable even in whole sleep (sensitivity: 83.40%; specificity: 72.08% in identifying slow activity epochs; correctly segmented SEMs: 93.24%; time misalignment: 0.49 s). The algorithm, being able to objectively characterize single SEMs, may be a valuable tool to improve knowledge of normal and pathological sleep.

1. Introduction

Slow eye movements (SEMs) are low frequency (0.1–1 Hz), conjugate, mainly horizontal bidirectional eye movements, variously described as 'drifting', 'rolling' or 'pendular'; SEMs are known to clinicians as characteristic of drowsy wakefulness and light sleep (sleep stages 1 and 2), typically peak at the sleep onset, and also occur during nocturnal awakenings and at the end of sleep [1]. SEMs have been also found in REM sleep and to a lower extent in sleep stages 3 and 4 [2].

Several studies correlated SEM activity with electroencephalographic (EEG) features of sleep onset (such as changes in alpha and theta power) [3–7], and with impaired behavioral performances typical of drowsiness and dozing-off [8,9].

Despite their potential relevance, a systematic analysis of SEMs in terms of their morphology and physical parameters (such as amplitude, duration and velocity) is still lacking, and so far few studies examined the properties of individual SEMs [10]. Visual identification and measurement of SEMs are time-consuming and prone to high inter-scorer variability given the scarce definition of SEMs as discrete events [11]. Indeed, differently from other phasic respiratory and motor events occurring during sleep, SEMs have not been included yet within the quantified phenomena occurring during sleep and are actually only supportive criteria for the visual identification of sleep stage 1 [11].

In recent years, we developed an automatic method for the off-line detection of SEM activity in electro-oculographic (EOG) recordings [12]. The method was based on the wavelet transform of the two EOG channels routinely used during polysomnography (PSG) [11,13], and identified SEM activity on the basis of EOG power redistribution toward lower frequencies [12]. The method was trained and validated against visual scoring on both 8 h and 24 h PSG recordings acquired in laboratory settings [2,12]. The method performed reliably in detecting the sleep onset in patients with obstructive sleep apnea syndrome (OSAS) compared to standard sleep onset criteria [14,15]. Moreover, the method was applied to quantify SEM distribution during the different sleep stages and across sleep cycles [16].

Despite the promising applications of our method, it suffers of an important drawback that may hamper its future use. Indeed, our

* Corresponding author. Tel.: +39 0547 339203; fax: +39 0547 339208.
E-mail address: filippo.cona2@unibo.it (F. Cona).

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previous method was conceived to detect intervals of SEM activity, identifying the initial and final instant of each interval, but without distinguishing the single eye movements within each detected interval. Therefore, it was neither suitable to count the number of individual SEMs, nor suitable to further characterize their physical properties. Actually, an objective automatized method for the detection and morphological measurement of single SEMs might be a valuable tool to improve our knowledge of normal and pathological sleep [10] and may contribute to furnish insights into their origin and function.

Purpose of this report is to present an advanced version of our method that: (i) may be used alternatively to the previous one in detecting intervals of SEM activity in EOG recordings (acquired both in laboratory and in real-world settings); (ii) is able to segment each identified SEM activity interval into the single movements; (iii) reliably extracts physical parameters (amplitude, velocity, duration) of each single detected SEM.

2. Materials and methods

2.1. Data and visual classification

The algorithm has been trained and validated on the basis of the visual identification of single SEMs performed by a sleep medicine expert on 24 h laboratory and real-life EOG recordings. In each recording, periods of about half an hour around the sleep onset and around the sleep offset (the periods during which SEMs are more frequent) were visually inspected by the sleep medicine expert who marked the beginning and ending instants of each recognized SEM; this classification was used to form a data set for algorithm training and testing on sleep onsets and offsets (Validation A, see Section 2.3). A further EOG sample of 80 min, selected uniformly across all recordings and across all sleep stages, was visually inspected by the expert for SEM recognition: this classification was used to obtain a test set for assessing algorithm performances over the whole sleep (Validation B, see Section 2.3). Data acquisition and the criteria for visual identification of SEMs are described in details in the Supplementary Material (Appendices A and B).

2.2. Detection algorithm

The training, testing and validation procedures of the algorithm are summarized in Fig. 1. The algorithm processes the EOG differential mode ($\Delta EOG(t) = EOG_R(t) - EOG_L(t)$, $EOG_R = E_2 - A_2$, $EOG_L = E_1 - A_1$), as the common mode is associated to noise or interferences.

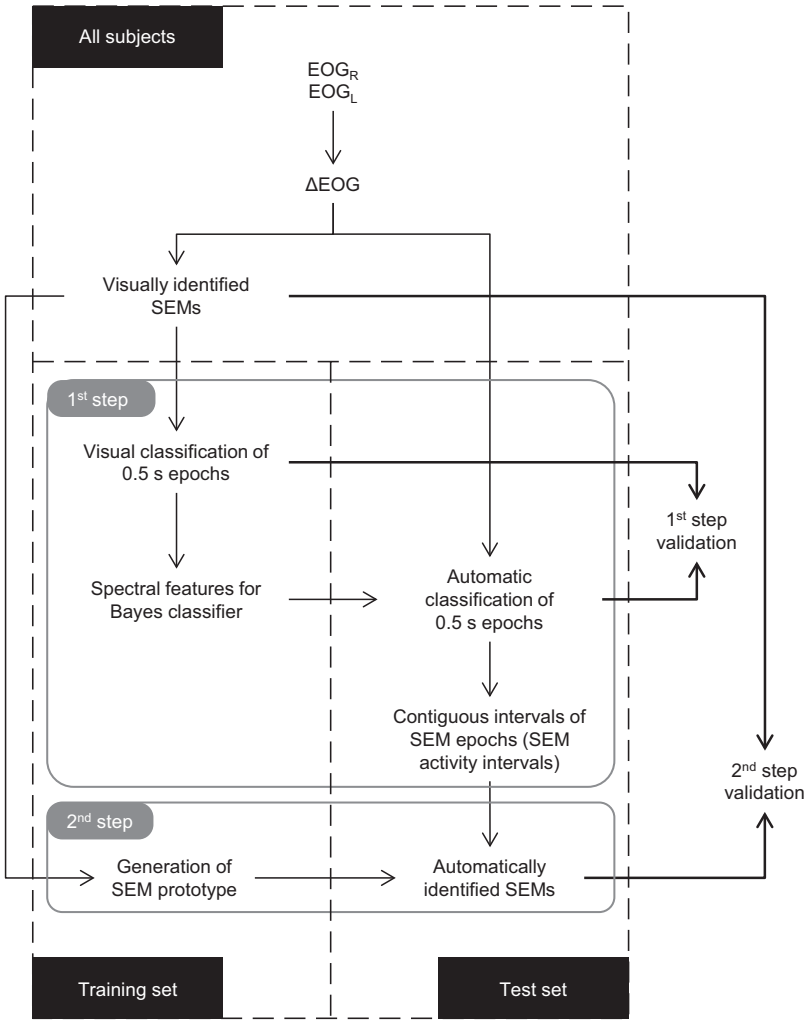

Fig. 1. Flow chart summarizing the training, testing and validation procedures. In Validation A, a leave-one-out cross validation procedure was adopted: in each session the training set consisted of the sleep onsets and offsets of 19 recordings while the testing set consisted of the sleep onset and offset of the remaining recording. In validation B, the training set consisted of the sleep onsets and offsets of all 20 recordings while the testing set consisted of the EOG sample of 80 min, randomly selected across all sleep stages (throughout the whole sleep) and across all recordings. Each validation procedure provides two sets of performances: performances in identification of 0.5 s SEM epochs and performances in segmenting SEM activity intervals (as consecutive 0.5 s SEM epochs) into single SEMs.