Automated Rapid Eye Movement Detector for Sleep Microstructure Classification

An Adaptive Quasi-Random Shot-Grouping Approach

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Introduction

REM sleep, characterized by transient rapid eye movement (REM) events, consists of two microstructures: tonic and phasic.[1,2] In human, the differentiation between the two microstructures relies on REMs which occur solely in phasic REM sleep.[3,4,5] Due to the time-consuming nature of visual scoring without automated REM detection, there has been limited assessment of the distinct neurophysiological mechanisms underlying these microstructures in humans.

We proposed an automated quasi-random shot-grouping approach to detect REM events for microstructure classification.[5] Mimicking the Human Genome Project,[6] the algorithm emulates visual REM scoring, treating the baseline EOG value as a "DNA strand" with EOG deflections as "bases". The extracted features are then utilized to identify REM events from artifacts, employing adapted thresholds that account for potential biases introduced during preprocessing.

Method

Polysomnography Setup

This study included 5 polysomnography recordings (with one designated for testing) randomly selected from the Montréal REM Sleep Behavior Disorder (RBD) cohort, The recordings included electrooculographic signals (EOG), recorded using the standard E1/E2 placement (A2 reference, sample rate=256Hz, sensitivity=7μV/mm). REM sleep was defined based on the AASM manual but irrespective of the electromyography signal amplitude, after the application of standard filters – a 60Hz anti-hum notch filter and a 0.3-100Hz bandpass filter.[7,8] Visual REM scoring was performed based on the recently proposed updates to the guidelines.[5]

Preprocess & Signal Derivates

To enhance eye movement signals (corneal-retinal dipole changes) captured by EOG, the original signals were

1) ***filtered*** (second-order zero-phase serial-pass elliptical filter; band-width: 1-10Hz): to remove artifacts of myogenic, encephalitic and cardiac sources without significantly altering the overall shape of the signals[5]
2) ***standardized*** (z-score): to mitigate variances in electrode sensitivity
3) ***smoothed*** (via moving average): to suppress any residual leakage
4) ***weighted***: to account for possible amplitude loss.

Subsequently, we computed two derivatives:

5) ***enhanced-REM*** (**dEOG**): acting as a template for potential REM events
6) ***enhanced-artifact*** (**sEOG**). to serve as a "binary" mask allowing the removal of potential artifact-induced dEOG mimics.

REM Detection

To mitigate the irregularities in REM characteristics (e.g., frequency, duration), we designed a system that mimics standard visual scoring. This quasi-random shot-grouping approach encompasses a series of procedures, with adjustable hyperparameters[$], automatically fine-tuned to account for biases introduced during preprocessing.

7) ***Peak Detection***: local maxima of deflection with amplitude z-score above 1.5 (for individual EOG) or above 3 (for dEOG and sEOG) with a 0.5-second[$] delay between peak detection. A threshold of 1.5 was used for sEOG when a single-channel artifact was present.
8) ***Border Detection***: zero crossing (over baseline trend) and local minima detected in signals were matched to estimate potential windows (representing the *edges of probable REM events*).
9) ***Classification***: to simulate visual scoring process, which evaluates various morphological criteria (e.g., deflection speed, absolute amplitude, deflection slope, etc.)
10) ***Adaptation & Repeat*****:** to detrend previously detected REMs within original signals and repeat the process till no more REM was found.

Results

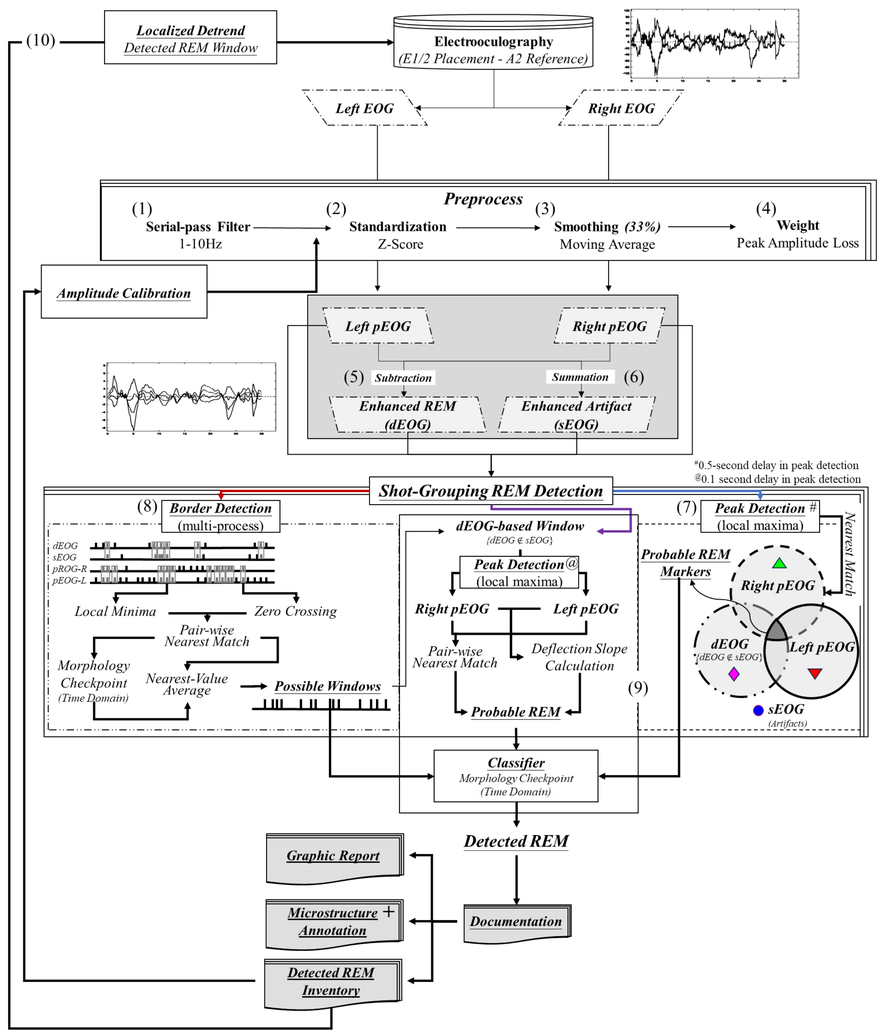

Figure 1. Diagram of the Adaptive Quasi-Random Shot-Grouping Classifier

The exhaustive inventory of REM events was obtained using a quasi-random shot-grouping classifier which adapts the information acquired from prior iterations and used it in the following iteration of signal preprocessing. The greedy algorithmic process terminates either when no further REM events are discernible or when the remaining signals exhibit similarity to their baseline trends. Each 3-second mini-epoch was then labelled as either tonic or phasic REM microstructure based on REM detection results of the REM detection process.

EOG: electrooculographic signals pEOG: preprocessed electrooculographic signals
REM: rapid eye movement

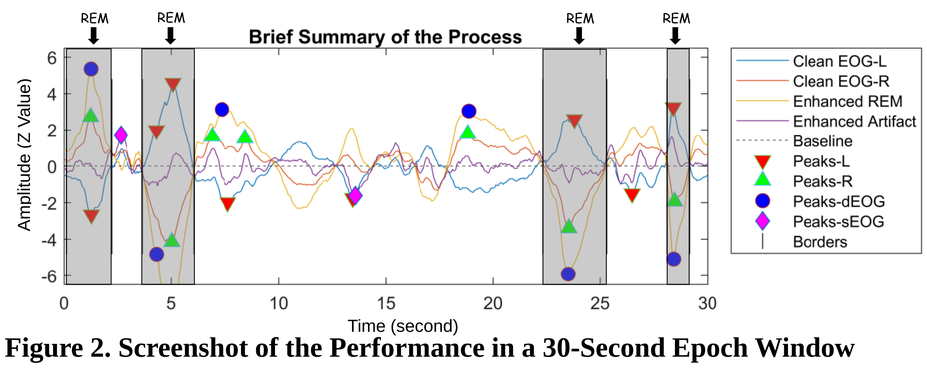

Figure 2. Screenshot of the Performance in a 30-Second Epoch Window

The top panel illustrated the REM window (shaded in grey) as detected by the algorithm from its "perspective", alongside with various peaks identified in EOG channels and their derivates.

Table 1 Classification Performance

	Sensitivity	Specificity	PPV	NPV
(in percentage)	84.3	93.8	91.1	88.9

The performance of the classifier was assessed in one recording with 4140 seconds of REM sleep.

PPV: Positive Predictive Value (True Positive/All Positives)
NPV: Negative Predictive Value (True Negative/All Negatives)

Discussion

Capitalizing on the abundance of artifacts resulting from the complex sleep comorbidities in patients with REM sleep behavior disorder, we developed an automated REM detector for sleep microstructure classification accounting for potential challenges associated with sleep disorders. The proposed method features its abilities in assessing recordings with varying electrode sensitivity, different artifact sources and abnormal sleep events.

The REM microstructure classification system demonstrated **high precision (91.1%)** while also maintaining a **negative predictive value of 88.9%** using 4140 seconds of REM. (Table 1) The system utilizes a quasi-random shot-grouping framework[6], which allows the system to detect REM using data-driven extracted features, instead of the traditional sliding-window-based sequential evaluation.[9] This approach demonstrates high efficiency, **with less than 20 seconds required per recording on average** (i5 8cores/internal graphic card, 16Gb RAM). This greatly reduces the time required for visual REM microstructure scoring (2-4 hours per recording by an experienced scorer).

Nonetheless, several limitations warrant consideration. First, the system might overlook certain small-amplitude REM events that are otherwise visible to the human eye. In addition, distinguishing between REM and large slow eye movements, often occurring at the end of a REM episode or between episodes – poses a challenge for the system

Besides REM detection and microstructure classification, the system also offers event-based REM window estimation without the conventional time constraint (e.g., 3-second epoch). Nonetheless, further testing and adjustments are required before the release of this open-source tool.

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