34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Automated Detection of Rapid Eye Movements in Children

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Abstract— **We present an automated multiple-step tool to identify Rapid Eye Movements (REMs) in the polysomnogram, based on modeling expert criteria. It begins by identifying the polysomnogram segments compatible with REMs presence. On these segments, high-energy REMs are identified. Then, vicinity zones around those REMs are defined, and lesser-energy REMs are sought in these vicinities. This strategy has the advantage that it can detect lesser-energy REMs without increasing much the false positive detections. Signal processing, feature extraction, and fuzzy logic tools are used to achieve the goal. The tool was trained and validated on a database consisting of 20 all-night polysomnogram recordings (160 hr) of healthy ten-year-old children. Preliminary results on the validation set show 85.5% sensitivity and a false positive rate of 16.2%. Our tool works on complete polysomnogram recordings, without the need of preprocessing, prior knowledge of the hypnogram, or noise-free segments selection.**

I. Introduction

Although the functions of sleep in human physiology are not completely known, there is abundant evidence supporting the idea that it plays a role in brain plasticity and memory consolidation [1]-[3]. Two different states have been defined: REM sleep (REMS) and non-REM sleep (NREMS) [4],[5]. These states are identified by the temporal concordance between EEG, electrooculographic (EOG) and electromyographic (EMG) patterns.

REMS is characterized by low-amplitude activity in the EEG, predominantly in the theta band (4-7 Hz) [6], centrally induced muscle atony [7], and the presence of rapid eye movements (REMs) in the EOG signal, these latter being the hallmark of the onset of REMS [4]. REMS has been associated with the development of procedural memory [8].

This work was supported in part by the Chilean Science and Technology Funding Agency, Chile, under Grants Fondo Nacional de Desarrollo Científico y Tecnológico Nº 1120319 and Nº 1110513. *Asterisk indicates corresponding author*

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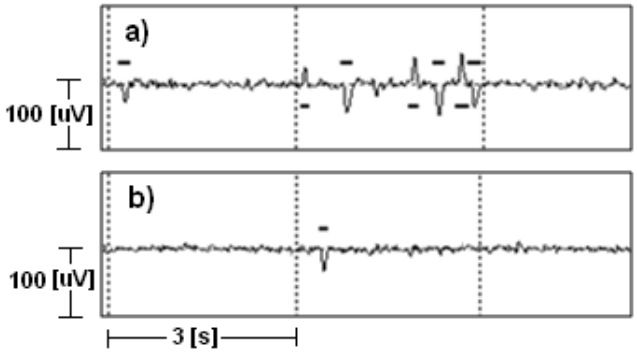

Figure 1: Examples of REMs in an EOG recording segment. The length of the horizontal line indicates the duration of each event. REMs are abrupt changes in the EOG signal, and they can occur in bursts (a) or as an isolated event (b).

REMs are abrupt changes in the EOG signal corresponding to spontaneous movements of the eyeballs during sleep. REMs usually occur as bursts [9] (fig. 1-a), but isolated events happen as well (fig. 1-b).

Visual detection of sleep patterns, including REMs, is a manual, time-consuming effort requiring a considerable level of expertise. In addition, it presents relevant intra- and inter-expert variability in detection [10],[11]. Automated detection of sleep patterns is a powerful tool to reduce the expert time devoted to this process and to standardize its outcome.

Different research groups have worked on automated REMs detection. Agarwal et al. [12] developed a method based on feature extraction and context information to detect REMs in ten healthy adult EOG recordings. The results in the testing data set showed 67.2% sensitivity (detection rate) and 24.5% false-positive (FP) rate. Värri et al. [13] compared five REMs detection algorithms on four healthy adult EOG recordings. Method A used EOG filtering and morphological criteria; method B used EOG filtering and activation and relaxation slopes of the signal; method C applied EOG filtering, context REMs feasibility and amplitude thresholds; method D applied cross-correlation between EOG channels and amplitude thresholds; and method E calculated the derivative of the EOG signal and used amplitude criteria. The best results were obtained applying method A: 90.0% sensitivity and a FP rate of 35.6%, and the poorest applying method B: 30.0% sensitivity and 49.3% FP rate. Hatzilabrou et al. [14] compared three methods in newborns: Method A applied amplitude and duration criteria; method B is an extension of method A, including the activation slope and correlation between EOG channels; method C used templates

representing typical REM shapes and autocorrelation with the EOG signal. The results on the testing data set showed 69.4% sensitivity for method B and 84.1% sensitivity for method C. Tsuji et al. [15] used Haar discrete wavelet transform on the EOG signal, obtaining 96.0% sensitivity and 22.0% FP rate. Barschdorff et al. [16] used EOG filtering and feature extraction, and neural networks, to detect REMs in four healthy children EOG recordings. The results on the testing data set showed 86.0% of correct detections.

The main objective of this work is to develop a novel tool for automated REMs detection based on modeling expert criteria. Additionally, we are building a significant annotated REMs database of all-night polysomnographic recordings of children for proper validation. In this paper we present preliminary results.

II. METHODS

A. *Recordings and database*

The database consists of 20 all-night polysomnogram recordings of healthy ten-year-old children, acquired at the Sleep Laboratory of the Instituto de Nutrición y Tecnología de los Alimentos (INTA), Universidad de Chile. It was divided in 15 recordings (total: 120 hr) for the training dataset (TS), and 5 recordings (40 hr) for the validation dataset (VS).

Sleep experts at the INTA Sleep Laboratory analyzed and marked the beginning and the end of the REM events using the visualization and marking tools of the Sleep-Analyzer. The Sleep-Analyzer is a tool, developed on MATLAB, to visualize and analyze polysomnographic signals, sleep patterns and hypnograms, applying signal processing tools, filters, etc.. The interactive graphic user interface allows to display, mark and review a selection of signals. This tool is developed by the Biomedical Engineering Laboratory of the Electrical Engineering Department, Universidad de Chile.

B. *REMs detection system*

Our automated detection system is based on expert procedures followed to detect REMs. They search for REMs in EOG recording zones which fulfill certain context conditions. Within these zones, they usually search for low-amplitude REMs in the vicinity of high-amplitude, well-defined REMs. The detection system consists of four modules (see Fig.2). Module I identifies the polysomnogram segments compatible with REMs presence. On those segments, module II searches for REMs candidates with amplitudes of 35 μV or more (REM_{35}), characterized by an artifact-free baseline and a steep activation slope, among others. Module III defines zones around REM_{35} to search for smaller REMs events, with amplitudes as low as 15 μV. Module IV identifies the smaller REM_{15} and generates the final REMs detection (start and end positions of each event). The thresholds for REMs detection, including the amplitudes of 35 μV and 15 μV for our 2-step detection, were empirically determined using the TS.

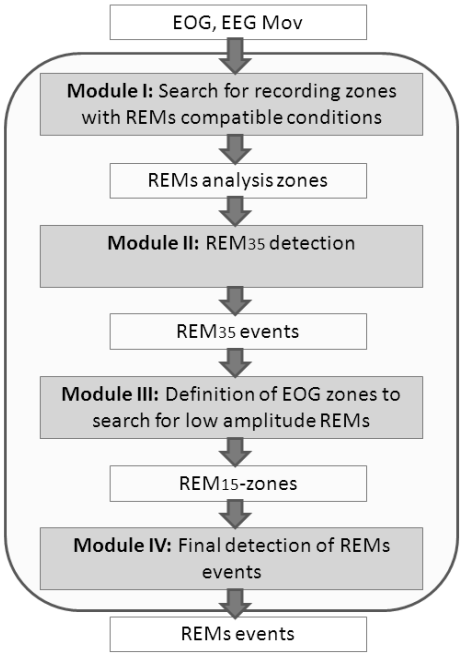

Figure 2: Block diagram of the proposed REMs detection system. The system is based on modeling sleep expert criteria to identify REMs events.

B.1 Module I: Search for recording zones with REMs compatible conditions

Module I seeks to identify recording zones with conditions compatible with REMs presence, which involves analyzing other polysomnogram channels. FFT is applied on the EEG signal using a 2.56-s moving Hamming window to determine the spectral power in the delta ([0,5; 3]Hz), theta ([3, 7]Hz), sigma ([10; 16]Hz), and "high frequency" ([30; 60]Hz) bands. The average power (*AP*) for 30-s EEG epochs obtained for each band: AP_D (delta), AP_T (theta), AP_S (sigma), AP_{HF} (high frequency) bands, and fuzzy classification rules are used to identify REMs compatible zones. Fuzzy rules include looking for zones with low AP_D (high AP_D is related to Slow Wave Sleep), low AP_S (high AP_S is related to Sleep Spindles, characteristic of stage 2 NREMS), high AP_T, (background activity characteristic of REMS), and low AP_{HF} (associated to contamination, noise, or wakefulness). Figure 3 shows an example of the EEG analysis and the result of module I for a training data set recording.

B.2 Module II: REM_{35} detection

Module II focuses on the zones defined by module I to identify REM_{35}. The EOG signal is filtered and the local minima and maxima are identified using sign changes in the slope of the signal, determined using linear regression on five consecutive samples. The signal amplitude of a REM candidate (REMC) is obtained considering the peak before and after the REMC (min-max-min or max-min-max). The consecutive peaks are identified by their amplitude-time coordinates (A_L, t_L), (A_C, t_C) and (A_R, t_R), the subindices standing for left, center and right, respectively. REMC with amplitude:

$$A_{REM} = \min\{|A_C - A_L|, |A_R - A_C|\} \geq 35\mu V$$

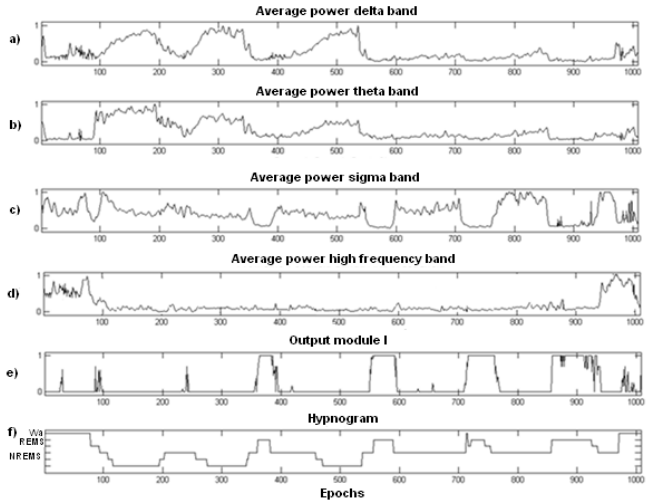

Figure 3: Example of the module I process. FFT is applied to obtain the moving average power for the: a) delta band ([0.5, 3] Hz), b) theta band ([3, 7] Hz), c) sigma band ([10, 15] Hz), and d) high frequency band ([30, 60] Hz). e) Result of module I, i.e. the recording zones where to focus the detection of REM_{35}. e) Hypnogram of the same recording (referential information).

qualify for further analysis. Four other features are calculated:

duration: $D_{REM} = (t_R - t_L)\,[s]$;

activation slope: $AS_{REM} = |A_C - A_L|/(t_C - t_L)\,[\mu V/s]$;

EOG RMS power: $RMS_{REM} = RMS_C/(1 + RMS_L + RMS_R)$; and body movement index: $BMI_{REM} = max\{RMS_{UppMov}, RMS_{LowMov}\}$.

Classification rules are applied on these features to generate the module output, i.e. the detected REM_{35} start and end positions throughout the EOG signal.

B.3 Module III: Definition of EOG zones to search for low amplitude REMs

Sleep experts search for smaller amplitude REMs events in the vicinity of well-established ones. Module III emulates this procedure, which we observed tends to reduce the risk of confusing smaller REMs and EOG artifacts. Low-amplitude REMs (REM_{15}) are sought only in a fuzzy vicinity of detected REM_{35}, defined as:

$$\mu_{Zone}(REM_{35}(t_C)) = \begin{cases} 1 & , \quad |t - t_C| \leq 60\ s \\ \dfrac{120 - |t - t_C|}{60} & , \quad 60 \leq |t - t_C| \leq 120\ s \\ 0 & , \quad OTHERWISE, \end{cases}$$

where $|t - t_C|$ is the temporal distance from the center of the REM_{35} to time t of the recording. If there are overlapped zones, these are integrated as:

$$\mu_{ZONE} = \cup\, \mu_{Zone}(REM_{35}).$$

Figure 4 shows an example of the REM_{15}-zone generation process. The membership degree to a REM_{15}-zone is a value in the range [0, 1].

B.4 Module IV: Final detection of REMs events

Module IV detects all REMs with amplitudes as low as 15 µV within the ranges set by module III, i.e. it includes the REM_{35} events previously detected:

$$REM_{15} = \{REM_{between\ 15\ \&\ 35\ \mu V} \cup REM_{35}\},$$

see figure 4. It starts by applying the same procedure used to generate the $REMC_{35}$ (module II), but modifying the amplitude threshold, according to the value of μ_{ZONE}. For $\mu_{ZONE} = 1$, the amplitude threshold is 15 µV. As the μ_{ZONE} value diminishes, the amplitude threshold increases, reaching 35 µV when $\mu_{ZONE} = 0$:

$$Amplitude\_thr(\mu_{ZONE}(t)) = -20 \cdot \mu_{ZONE}(t) + 35\ \mu V$$

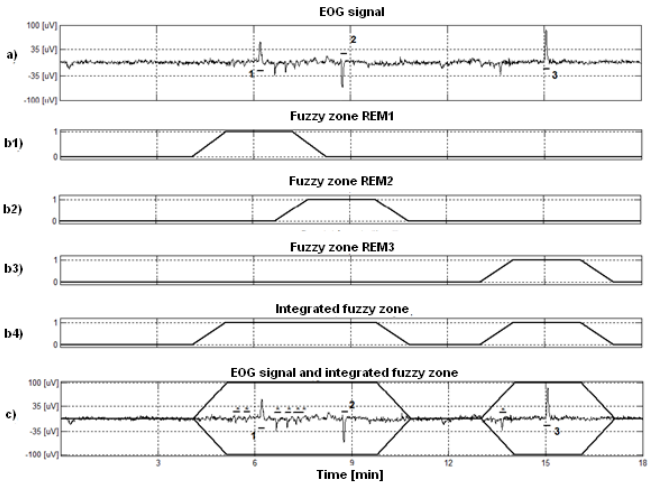

Figure 4: REM_{15} detection sequence: a) EOG signal including 3 REM_{35} identified by module II, labeled 1, 2 and 3. b1, b2 y b3) fuzzy REM_{15}-zones for REM_{15} search, defined by each REM_{35} previously detected; b4) integrated REM_{15}-zone, created by merging the three previous zones. c) Superposition of the REM_{15} fuzzy search zones and the EOG signal; REM_{15} are only sought within the zones limits, and findings are marked.

The features A_{REM}, D_{REM}, AS_{REM}, RMS_{REM}, BMI_{REM} are calculated on the $REMC_{15}$, using the algorithms described in module II. Two additional features are calculated: the correlation factor (CF_{REM}), which correspond to the correlation between $REMC_{15}$ and a prototype "ideal" REM event; and the EMG polysomnogram channel RMS power (RMS_{EMG}). The variables characterizing each $REMC_{15}$ are used as inputs to a decision tree [17] to obtain the final output of the system.

II. Results

The system was trained and the parameters were adjusted using the TS. To measure the performance of the system we used the VS. The overall results for each dataset for continuous all-night sleep recordings are presented in Table I.

III. Discussion and Conclusion

For the VS the system shows sensitivity for continuous all-night sleep recordings of 88.9% and a FP rate of 16.2%.

TABLE I. AUTOMATED REMS DETECTION RESULTS ON TRAINING AND VALIDATION DATASETS

Set	REM events		Expert-system agreement in REM events (TP)	Marked, but not detected (FN)	Detected, but not marked (FP)	Sensitivity [%]	False positive rate [%]
	Marked by experts	Automated detection					
Training	12403	12518	11212	1191	1306	88.9	12.6
Validation	5813	6015	5212	601	803	85.5	16.2

The results show a good performance of the detection tool. Further tests and improvements are programmed. Our detection approach has the advantage that it does not need preprocessing of the recordings, such as previous knowledge of the hypnogram, or selecting noise-free segments.

Automated REMs pattern detectors are a relevant contribution to reduce expert observation time and standardize criteria among evaluators. This proposed REMs detection system is part of a larger ongoing project to develop different tools oriented to support sleep studies in children, including sleep classification algorithms [18]-[21], automatic sleep-spindle detection in children at different ages [22]-[24]; and a visualization and analysis system for children polysomnographic recordings, integrating the developed tools, the *Sleep-Analyzer*.

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