Dual Approach for Automated Sleep Spindles Detection within EEG Background Activity in Infant Polysomnograms

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Abstract—An automated system for sleep spindles detection within EEG background activity, combining two different approaches, is presented. The first approach applies detection criteria on the sigma-band filtered EEG signal, including fuzzy thresholds. The second approach mimics an expert’s procedure. A sleep spindle detection is validated if both approaches agree. The method was applied on a testing set, consisting of continuous sleep recordings of two patients, totaling 1132 epochs (pages). A total of 803 sleep spindles events were marked by the experts. Results showed an 87.7% agreement between the detection system and the medical experts.

Keywords— EEG, infants sleep, pattern recognition, sleep spindles

INTRODUCTION

The study of sleep characteristics and their related patterns can be used for different purposes in human physiology [2],[9],[17]. For instance, sleep studies in children are used in the neurofunctional evaluation of the central nervous system, nutritional deficiencies, or the evaluation of risk for SIDS (Sudden Infant Death Syndrome) [6],[15],[16],[18]. Polysomnographic recordings are powerful tools for the analytical study of sleep, since several activities are recorded simultaneously. Traditionally, the sleep expert searches visually for characteristic patterns in the electroencephalogram (EEG), the electrooculogram (EOG) and the electromyogram (EMG); additional signals, such as the electrocardiogram (EKG), and channels for body movements, oxygen saturation and body temperature, are useful as contextual information. The sleep state is then classified as Quiet-NREM Sleep (QS) or Active-REM Sleep (RS), according to the temporal concordance of relevant EEG, EOG and EMG criteria, and QS is divided in four stages, according to EEG patterns.

The visual pattern detection in polysomnograms by sleep specialists is a time-consuming effort. The automated detection has the potential to be of great help for both physiological and pathological studies. It allows criteria unification, and quantitative and statistical analysis unfitted to manual processes. In our sleep classification research [5],[11] we have included 5 characteristic patterns for sleep classification: Slow delta and theta waves in the background activity of the EEG, presence of sleep spindles in the EEG, rapid eye movements in the EOG and muscular tone in the EMG. Other context information, such as body movements, is also used as input.

The research on isolated patterns contributes to an adequate classification of sleep stages, but also has an interest in itself. Sleep spindles (SS) are transient events occurring during sleep observable mainly in the anterior channels of the EEG. They are a sequence of sigma (fast) waves. The presence of the first SS event indicates the onset of QS stage 2 (QS-2), although they only need to appear sporadically to determine the ongoing status of QS-2. The SS are usually mounted on other slower waves with larger amplitudes in the EEG. EEG itself is a noise-riddled signal.

The interest in sleep spindles lies not only in its unique association to the onset of QS-2, but also in other interesting findings, such as those relating SS and normal aging [3], infant pathologies or sleeping positions [12], and memory processes [7]. Recent neurophysiological findings associate SS to variations in membrane potentials in the thalamocortical network, pointing to a close relation between changes at a neuronal level and the macroscopic EEG, with a reciprocal relationship between SS and slow (delta) waves [4].

The automated detection of SS has been tackled by different research groups. Huupponen et al. [13] describe an adaptive module to establish an optimal amplitude threshold to detect SS; the best reported performance is 84.9% success. Akgül et al. [1] apply time and frequency analysis to characterize SS, but do not report a classification performance. Gorur et al. [8] apply short time Fourier transform and neural networks, using both multilayer perceptron (MLP) and Support Vector Machine (SVM). Tests were performed on equally distributed, in SS and non-SS, examples sets. A MLP showed a 88.7% success on 1142 examples, and a SVM showed a 95.4% success on 175 examples. They do not report results using real recordings.

In our previous work [5],[11] we used a time-domain analysis, including period, amplitude and symmetry to detect SS compatible signals. Neighbouring signals were grouped together in trains as candidate SS, and validated according to a quality index. The systems was aimed at sleep classification, therefore the algorithm output was a single index in each epoch for SS presence. Since SS episodes, even 5 minutes apart, are enough to determine QS-2 [10], the system included several rules to avoid false positives, such as more stringent requirements for isolated SS candidates.
In this paper we used an approach which combined a modified version of our previous algorithm, which mimics an expert’s procedure on SS detection [5], and a time-based fuzzy logic-approach on the sigma-band filtered EEG signal. We applied the method to real continuous sleep recordings of infants.

METHODS

Each channel of the EEG was sampled at a 250 Hz rate. Two SS discrimination approaches were processed in parallel: Module 1 applied detection criteria on the sigma-band filtered EEG, and module 2 applied an expert-mimicking approach. In each module, the original EEG signal was filtered and then analyzed in the time domain, using different criteria. The outputs of both modules were fed to module 3, which combined both outputs and determined the presence of SS. Several parameters were tuned using training data in order to establish adequate thresholds.

There isn’t a single definition about the band allowed for SS, for example, some authors use bands as wide as 10-16 Hz [13], whereas others constrain it to 11-15 Hz [12] or 12-15 Hz [7].

The parameters were adjusted using a total of 358 SS events, characterized by the experts. The recordings were made continuously on a TECA 1A97 18-channel polygraph. The EEG electrodes were placed adapting the international 10-20 system for infants (FP1-C3, C3-O1, FP2-C4, C4-O2 and C3-C4). We used only 4 derivations: two anterior derivations (FP-C: channels 1 and 3), and two posterior derivations (C-O: channels 2 and 4).

Module 1

Fig. 1 shows a block diagram of module 1, and Fig. 2 shows an example of the creation of a candidate window in module 1.

EEG signals not corresponding to the sigma band were filtered out by a 6-th order Butterworth, 10-15 Hz band-pass filter. The signal amplitude was obtained after identifying 3 consecutive peaks. A linear regression algorithm, in the same fashion as described in module 2, was applied in order to avoid false local peaks. A fuzzy amplitude threshold, $FAp(h)$, where $h$ is the amplitude in µV, was tuned to discriminate candidate pulse waves, establishing $FAp(h<13.15µV)=0$, $FAp(h=13.5µV)=1$, and $FAp(h)=(h-13.15)/0.35$ for the transition. A sleep spindle is a train of sigma waves; hence consecutive candidate pulses were chained together in a candidate window. The weighted amplitude assigned to the candidate window, $WA=(\sum FAp_i * t_i)/t_w$, where $t_i$ is the duration of the pulse candidate $FAp_i$ and $t_w$ is the window time span, $\sum t_i \leq t_w$, punished candidate pulses which were further apart from each other. An absolute limit was set at 0.18 s. On a later step, candidate windows generated in this way and lasting less than 0.58 s were discarded. The surviving windows were the output of module 1.

Module 2

A block diagram of module 2 is shown in Fig. 3, and Fig. 4 shows an example of SS detection in module 2.

Low frequency components of the EEG signal were preserved by pre-processing using a 10-th order digital FIR comb filter, with a cutoff frequency of 17 Hz. Sigma band detection was based on time domain analysis. Three consecutive peaks (min-max-min or max-min-max) were established by three consecutive sign changes in the slope of the signal, determined using linear regression on 5 consecutive samples. The consecutive peaks were identified by their amplitude-time coordinates $(A_L, t_L), (A_C, t_C)$ and...
In order to avoid false positives due to noise caused by body movements, the corresponding channel was sampled during wakefulness (usually at the beginning of the recording session) and a threshold was established.

**Module 3**

SS presence required simultaneous detection in both modules 1 and 2. The product was used as t-norm to combine both inputs, and near-by trains (less than 0.8 s apart) were bonded together. Candidates lasting less than 0.5 s were discarded. In order to consider register- and channel-specific conditions, the biggest amplitude, \( \max(A_{ch}) \), and the average duration, \( t_{ch} \), of all trains in the channel was obtained. The threshold for SS validation was set at \( 0.6 \times \max(A_{ch}) \times t_{ch} \).

**RESULTS**

Only the anterior derivations of the testing set were considered (channels 1 and 3). Usually, posterior derivations are the primary reference for background activity, and the anterior derivations are preferred for SS detection [5]. In our experience, much less SS appeared in the posterior derivations.

The system was tested on continuous sleep recordings of two patients, totaling 1132 epochs (pages). There were 803 SS events marked by the experts. The results for each recording are shown in table I, and the global results are shown in table II.

### Table I

**SLEEP-SPINDLES DETECTION RESULTS ON EACH RECORDING OF THE TESTING DATA SET**

<table>
<thead>
<tr>
<th>Channel</th>
<th>SS events</th>
<th>Expert marked</th>
<th>Automated detection</th>
<th>System agreement</th>
<th>Marked, but not detected</th>
<th>Detected, but not marked</th>
<th>Expert agreement rate</th>
<th>System precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>283</td>
<td>265</td>
<td>260</td>
<td>33</td>
<td>5</td>
<td>0.931</td>
<td>96.1%</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>227</td>
<td>213</td>
<td>193</td>
<td>34</td>
<td>20</td>
<td>0.950</td>
<td>96.6%</td>
<td></td>
</tr>
</tbody>
</table>

### Table II

**TOTAL RESULTS OF THE AUTOMATED SLEEP-SPINDLES DETECTION ON THE TESTING DATA SET**

<table>
<thead>
<tr>
<th>Recording</th>
<th>SS events</th>
<th>Expert marked</th>
<th>Automated detection</th>
<th>System agreement</th>
<th>Marked, but not detected</th>
<th>Detected, but not marked</th>
<th>Expert agreement rate</th>
<th>System precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>C001493</td>
<td>520</td>
<td>478</td>
<td>453</td>
<td>67</td>
<td>20</td>
<td>0.971</td>
<td>96.8%</td>
<td></td>
</tr>
<tr>
<td>AM107003</td>
<td>263</td>
<td>206</td>
<td>251</td>
<td>33</td>
<td>27</td>
<td>0.971</td>
<td>97.2%</td>
<td></td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td><strong>883</strong></td>
<td><strong>786</strong></td>
<td><strong>704</strong></td>
<td><strong>99</strong></td>
<td><strong>62</strong></td>
<td><strong>0.971</strong></td>
<td><strong>97.2%</strong></td>
<td></td>
</tr>
</tbody>
</table>
DISCUSSION

According to the testing set results, the automated system detected most of the SS events, with an overall performance of 87.7% of expert agreement, and a 91.9% precision.

These results cannot be directly compared with our previous SS detection algorithm [5], because that was aimed at sleep stages classification and hence just associated an SS presence index per epoch (20 s page), but did not detect individual events.

Our detection system shows the ability to detect each SS event in a continuous polysomnographic recording.

ACKNOWLEDGMENT

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REFERENCES