Automated Detection of Apnea/Hypopnea Events in Healthy Children Polysomnograms: Preliminary Results

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***Abstract*— A methodology to detect sleep apnea/hypopnea events in the respiratory signals of polysomnographic recordings is presented. It applies empirical mode decomposition (EMD), Hilbert-Huang transform (HHT), fuzzy logic and signal preprocessing techniques for feature extraction, expert criteria and context analysis. EMD, HHT and fuzzy logic are used for artifact detection and preliminary detection of respiration signal zones with significant variations in the amplitude of the signal; feature extraction, expert criteria and context analysis are used to characterize and validate the respiratory events. An annotated database of 30 all-night polysomnographic recordings, acquired from 30 healthy ten-year-old children, was divided in a training set of 15 recordings (485 sleep apnea/hypopnea events), a validation set of five recordings (109 sleep apnea/hypopnea events), and a testing set of ten recordings (281 sleep apnea/hypopnea events). The overall detection performance on the testing data set was 89.7% sensitivity and 16.3% false-positive rate. The next step is to include discrimination among apneas, hypopneas and respiratory pauses.**

I. Introduction

Under normal conditions pharyngeal muscles maintain the upper airway permeable and allow air circulation towards the lungs. Although these muscles are relaxed during sleep, the upper airway remains open enough to allow adequate air circulation. However, in some people the passage is narrower, which may cause complete or partial air flow obstruction towards the lungs due to muscle relaxation during sleep.

Sleep-related breathing disorders (SRBD) can be classified from the respiratory patterns that occur during sleep. The most characteristic SRBD are repetitive upper airway obstructions during sleep. If the obstruction is complete and therefore there is no airflow, it's called apnea, whereas if the obstruction is partial, resulting in a reduction of airflow, it's labeled as hypopnea [1]. Other relevant SRBD are respiratory effort related arousals (RERAs), in which the patient shows a progressive increase in the respiratory effort that ends with arousal. SRBD are correlated with sleep disruption, fatigue, sleepiness, and decreased attention and concentration capabilities [2], as well as impaired quality of life, increased accident risks, and depressed cognitive functions. Several pathologies are associated with SRBD, including hypertension and cardiovascular disease. Reliable identification of these patterns is critical for case identification and disease severity estimation [1].

Different research groups have worked on automated respiratory pattern detection. Waxman et al. [3] used a LArge Memory Storage And Retrieval (LAMSTAR) neural network and wavelets transform for feature extraction on six physiological signals obtained from 30-s segmented polysomnogram recordings to predict apnea and hypopnea in healthy adult recordings. The method was tested during non-REM and REM sleep. The best prediction performance was obtained during non-REM sleep, showing 80.6% and 74.4% sensitivity, and 72.8% and 68.8% specificity for apnea and hypopnea prediction, respectively. Tian and Liu [4] applied a time delay neural network (TDNN) on airflow and SaO2 signals to detect apnea and hypopnea events on 30 adult all-night recordings (15 used for training and 15 used for testing). The results in the testing data set showed 90.7% and 80.8% sensitivity, and 86.4% and 81.4% specificity rate for apnea and hypopnea detection, respectively. Authors note that the changes in SaO2 show an important delay with respect to the airflow signal. Fontenla-Romero et al. [5] developed a method to discriminate obstructive, central and mixed apneas, based on artificial neural networks (ANN) and wavelet transform. To train and test the system, 120 events from selected segments of six recordings were used, obtaining 83.8% classification accuracy. Varady et al. [6] developed a signal classification method to detect on-line respiratory patterns (normal breathing, hypopnea, and apnea) based on the preprocessed respiration signal and ANN. The test was applied on 30 5-min segments from 16 different adult recordings, obtaining 90% of detection performance. Mijović et al. [7] applied ensemble empirical mode decomposition (EEMD) on the EKG signal to obtain intrinsic mode functions (IMFs), amplitudes and frequencies for each IMF. Linear discriminant analysis was used to classify obstructive sleep apnea events. Test results (25 recordings) showed 89% sensitivity and 83% accuracy. Mietus et al [8] presented an automated method to quantify sleep apnea from EKG segments. This method applies Hilbert transform (HT) to determine the instantaneous amplitude and frequency, and establishes thresholds criteria. Testing performed on the Computer in Cardiology sleep apnea dataset showed 84.5%

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sensitivity. Otero et al. [9] developed a method to identify apneas and hypopneas using oxyhemoglobin saturation (SpO2) introducing fuzzy logic to represent medical knowledge. Five adult recordings (41 hours, with 881 apneas and 316 hypopneas) were used to evaluate the method, showing 96% sensitivity and 6% false-positive (FP) rate for apnea detection, and 92% sensitivity and 8.7% FP rate for hypopnea detection. Restrepo [10] used Biopac's abdominal strain gauge to collect segments of respiratory signals. The algorithm combines autoregressive (AR) models and a fuzzy logic classification scheme to detect normal respiration, respiration with artifacts or apneas. Experimental results showed that fuzzy logic provides a flexible and adaptable classification mechanism to reduce false alarms.

The main objective of this work is to develop a novel method for automated detection and characterization of sleep apnea/hypopnea events in children based on advanced signal processing algorithms, expert criteria and multi-channel context analysis. In this paper we present preliminary detection results, without differentiating among patterns types. Additionally, we are building a significant annotated sleep patterns database of all-night polysomnographic recordings of children for proper validation, that includes: respiratory patterns (obstructive apnea, central apnea, mixed apnea, hypopnea, respiratory pause, RERA and snore), sleep spindles (SS), rapid eye movements events (REMs), cyclic alternating patterns (CAP), and background EEG activity.

II. Methodology

A. Subjects, Recordings and Database

The database consists of 30 all-night polysomnographic recordings acquired from healthy ten-year-old children at the Sleep Laboratory of the Instituto de Nutrición y Tecnología de los Alimentos (INTA), Universidad de Chile. The recordings were performed using an Easy EEG-II 32-channel polygraph (Cadwell, WA, USA, 2000). Each channel was sampled at a 200 Hz rate and saved in EDF format for offline analysis. Neural networks were applied to separate the database in 15 recordings for the training set (TS, 485 sleep apnea/hipopnea events), five recordings for the validation set (VS, 109 sleep apnea/hipopnea events), and ten recordings for the testing set (281 sleep apnea/hipopnea events).

Sleep experts at the INTA Sleep Laboratory marked the beginning and the end of each sleep apnea/hypopnea event using the visualization and marking tools of the Sleep-Analyzer software [11] (Fig.1). The Sleep-Analyzer is a tool, developed in MATLAB®, to visualize and analyze polysomnographic signals, sleep patterns and hypnograms. This tool is being developed by our group at the Electrical Engineering Department in collaboration with the Sleep Laboratory, INTA, both from the Universidad de Chile.

B. Sleep Apnea/Hypopnea Events Detection System

The method is organized as a cascade of four modules, as shown in Fig.2. It does not need preprocessing of all-night polysomnograms, automatically sorting out each sleep apnea/hypopnea event position throughout the recording.

Module I applies artifact detection and signal processing tools including empirical mode decomposition (EMD) [12], Hilbert-Huang transform (HHT) [13] and fuzzy logic on the respiratory signal to estimate the quality of the recording, and to detect the zones with significant variations in the amplitude of the respiratory signal, compatible with SRBD. Module II focuses on the selected zones to generate sleep apnea/hypopnea candidate events using feature extraction. Module III applies expert criteria and multi-channel context analyses to validate and characterize the detected respiratory events (start and end positions). Module IV is a classification system to discriminate among the different manifestations, based on expert knowledge. This module is currently under construction, and is not included in the results shown in this paper.

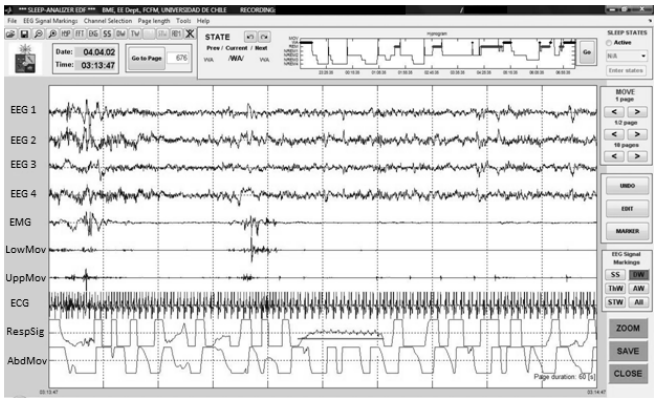

Fig. 1. The Sleep-Analyzer is a computational system to visualize polysomnographic recordings; to detect, mark, process and analyze sleep patterns and hypnograms. The figure shows one visualization window, which includes a set of channels (EEG, EMG, body movements, EKG, respiratory signal and abdominal movements), the hypnogram, patient information and control buttons. In this example one can see an obstructive apnea event marked by the medical expert on the RespSign channel.

B.1 Module I: Detection of respiratory signal zones with significant amplitude variations

Module I consists in two stages and allows to focus the sleep apnea/hipopnea detection in the compatible zones of the respiratory signal.

The first stage applies artifact detection based on root mean square (RMS) power analysis on the respiratory signal and duration criteria to determine whether the quality of each

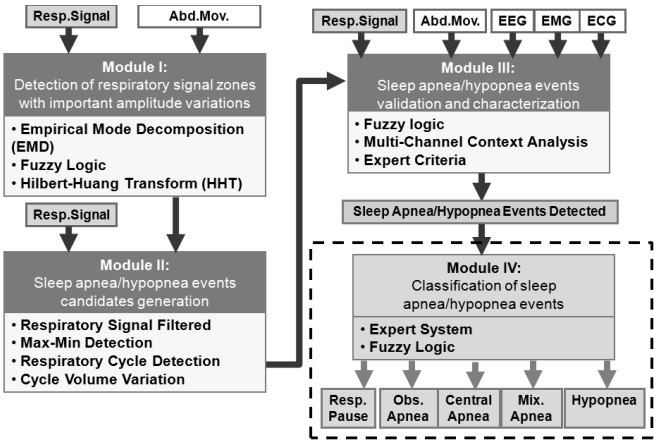

Fig. 2. Block diagram of the proposed sleep apnea/hypopnea events detection system. Modules I to III allow the detection of SRBD signals without discriminating the pattern types. This paper describes these results. The dashed line shows module IV, which is currently being implemented, and that will allow the classification of each event in its corresponding category.

30-s window of respiratory signal is compatible with SRBD detection. Using classification rules, each window is qualified as: good, acceptable or poor. Poor windows are discarded from further analysis.

In the second stage, SRBD compatible zones detection is applied to determine the zones where the respiratory signal amplitude decreases significantly. EMD is applied as a bank of filters on the respiratory signal using a 10-s moving window to decompose the signal in a series of components called intrinsic mode functions (IMFs). The EMD separates, in an iterative form, a time series in high-frequency components (IMF) and a lower frequency component or residue. Fig. 3 shows an application example of EMD on a segment of respiratory signal. HHT is used to determine instantaneous amplitude (*a(t)*) and instantaneous frequency (*w(t)*). Fuzzy logic is applied to model *a(t)* and *w(t)*; classification rules are used to define the analysis zones (empirically determined using the TS).

B.2 Module II: Sleep apnea/hypopnea candidate events generation

Module II applies feature extraction criteria on the zones defined by module I to generate the respiratory event candidates.

The respiratory all-night signal is filtered and the minima and maxima are identified, using sign changes in the signal slope (determined by linear regression) and duration criteria. Three consecutive peaks: min–max–min are identified by their amplitude-time coordinates (A_L, t_L), (A_C, t_C) and (A_R, t_R), define the respiratory cycle. The sub indices stand for left, center and right, respectively (see Fig.4).

The following features are calculated for each respiratory cycle: amplitude: $A_{cycle} = \min\{|A_C - A_L|, |A_R - A_C|\}[\mu V]$; duration: $D_{cycle} = (t_R - t_L)[s]$; base line: $BL_{cycle} = \frac{(A_R - A_L)}{(t_R - t_L)}(t - t_L) + A_L$; volume: $V_{cycle} = \sum_{i=1}^{N} \left| A(t_i) \times \left(\frac{(A_R - A_L)}{(t_R - t_L)}(t_i - t_L) + A_L \right) \right|$; and the volume variation defined in each 10-s moving windows: $\Delta V_{cycle} = \frac{\sigma_{V_{cycle}(10s\ window)}}{\overline{V_{cycle}(10s\ window)}}$.

Empirical threshold values and detection rules based on expert criteria are applied on these features to generate the sleep apnea/hypopnea event candidates.

B.3 Module III: Sleep apnea/hypopnea events validation and characterization

Module III is used to validate and characterize the sleep apnea/hypopnea candidate events generated by module II. The method is based on expert criteria and multi-channel context analysis, the aim is to mimic the expert procedure during visual detection of sleep respiratory patterns.

Sleep experts detect a SRBD event candidate on the respiratory signal and then apply a multi-channel context analysis, including other polysomnographic signals (EEG, EMG, body movements, EKG and abdominal movement). Fig. 5 shows an example of the context information for expert analysis: the respiratory signal shows an apnea/hipopnea candidate. One could classify the event as an apnea, but the context analysis unveils that other signals

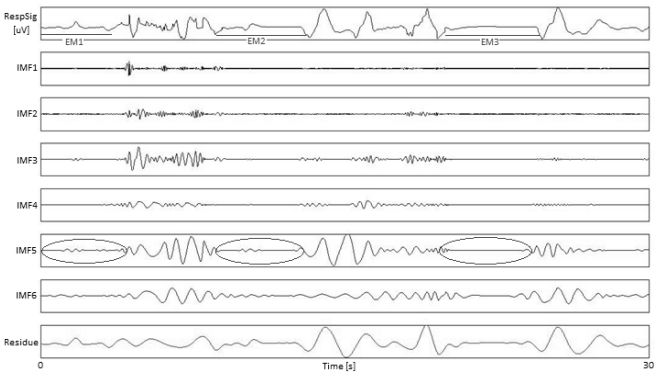

Fig. 3. Example of the application of EMD on a respiratory signal. The original respiratory signal is in the graph at the top (RespSign). It shows three sleep apnea/hypopnea events marked by the sleep expert (EM_i). IMF5 unveils sleep apnea/hypopnea events (circles) behavior.

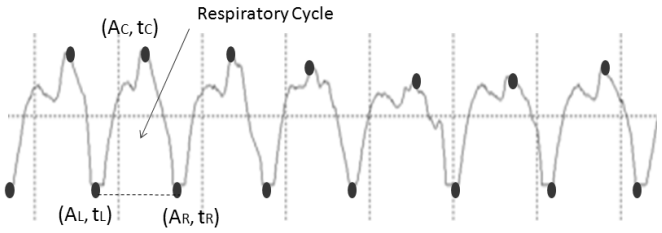

Fig. 4. Minima and maxima signal identification to establish the respiratory cycles.

present significant artifacts, dismissing the initial classification.

Features for other polysomnographic channels are determinated: EEG amplitude: $A_{EEG} = \min\{|A_C - A_L|, |A_R - A_C|\}[\mu V]$; normalized RMS power: $RMS = \frac{RMS_C}{(1+RMS_L+RMS_R)}$ for EEG (RMS_{EEG}), abdominal movements (RMS_{Abd}) and EMG (RMS_{EMG}); movement index: $BMI = \max\{RMS_{UppMov}, RMS_{LowMov}\}$; and EEG spectral power in the alpha ([7, 13] Hz) and "high frequency" ([30, 60] Hz) bands to detect arousals. Classification rules are applied on these features to generate the output of this module, i.e. initial and end positions of each sleep apnea/hypopnea event throughout the night.

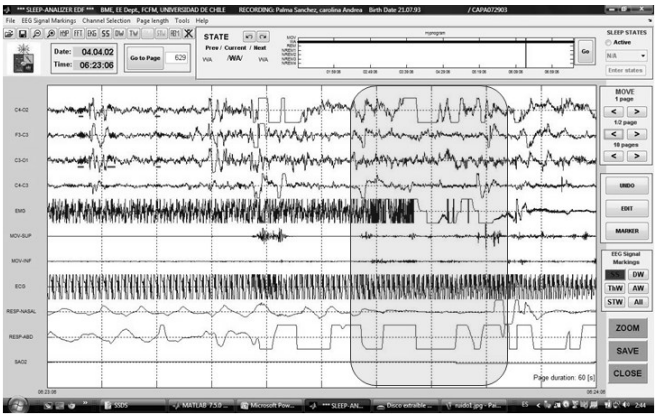

Fig. 5. Example of context information for expert criteria in multi-channel polysomnographic analysis. The use of context information means looking at other channels to determine if an apnea/hypopnea candidate corresponds to a real event (RESP NASAL). In this case, the presence of high frequency contamination in the EEG, EMG saturation and artifacts in the body movement channel convey that the candidate found in the respiratory signal cannot be classified as a respiratory event.

TABLE I. AUTOMATED SLEEP APNEA/HYPOPNEA EVENTS DETECTION.

Set	Sleep Apnea/Hypopnea Events		Expert-system agreement (TP)	Marked, but not detected (FN)	Detected, but not marked (FP)	Sensitivity [%]	False-positive rate [%]
	Marked by expert	Automated detection					
Training	485	519	439	46	80	90.5%	15.4%
Validation	109	119	98	11	21	89.9%	17.6%
Testing	281	301	252	29	49	89.7%	16.3%

III. RESULTS

The system was trained and the parameters were adjusted using the TS and VS. The performance of the system was measured using the testing dataset. The overall results are presented in Table I.

IV. DISCUSSION AND CONCLUSION

The system obtained a sensitivity of 89.7% and a FP rate of 16.3% for the testing dataset. We consider it a good performance of the detection tool. However, further tests and improvements are under way. Comparing our results with others revised in the introduction, the ones obtained by Otero et al. [9] show a better performance. However, in our experience the use of SpO2 information generates an important delay in detection of the beginning of the event. In the same line, Tian and Liu show that as the SaO2 changes are commonly delayed by 10 or more seconds compared to the airflow signal [4].

On the other hand, sleep patterns detection in infants and children is a complex and not effectively explored task [14]. Most research in the literature apply their work on adult recordings [3]-[10]. Children polysomnograms present an important level of noise and artifacts, and the patterns, including apnea/hypopnea events, are not necessarily that well established as in adults. For example, children and adolescents with obstructive sleep apnea have fewer EEG arousals than adults with obstructive sleep apnea. Indeed, obstructive apneas and hypopneas in children and adolescents often do not cause EEG arousals. The total arousal index is frequently only modestly elevated in children with obstructive sleep apnea syndrome. For instance, in preschoolers not more than half of obstructive apneas were associated with arousals [15].

Detection and characterization in children recordings is the main contribution of this work. In addition, the proposed approach has the advantage that it does not need preprocessing of the recordings or selecting noise-free segments. An automated sleep apnea/hypopnea pattern detector is a relevant contribution to reduce expert visual analysis time and to standardize criteria among evaluators.

This proposed detection system is part of a larger project to develop different tools oriented to support sleep studies in children, including sleep classification algorithms [16],[17], automatic SS detection in children at different ages [18],[19], REM events identification [20], integrated in a visualization and analysis system, the Sleep-Analyzer [11].

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