SLEEP APNEA DETECTION BY POLYSOMNOGRAPHIC ANALYSIS

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Abstract: The paper presents a new method, based time-frequency analysis, i.e. wavelet transform, to detect the respiratory problems occurring when polysomnographic sleep monitoring is performed. The EMG Chin (or Submental EMG) is one of the polysomnographic signals recorded in order to identify respiratory problems of the patients. After the submental EMG (SM EMG) is cleaned of power line interference, it is further analyzed using the wavelet transform to extract the apnea episodes. The correlation with the sound signal recorded by a microphone is performed to identify the snoring episodes, which show up also in segments with an increased amplitude in EMG Chin.

Introduction

Obstructive Sleep Apnea (OSA) is a disease in which the respiratory airways involuntarily collapse during sleep, leading to serious consequences. An OSA attack is characterized by repeated episodes of upper airway closure during sleep and is defined as the total cessation of respiratory airflow that lasts at least for 10 s. It has been proven that the patients affected by OSA are generally exposed to hypertension, ischemic heart diseases and stroke [1]. OSA is often accompanied by daytime sleepiness, which includes the danger of industrial accidents, driving problems and decreasing of the work quality.

That is why the patients are usually under observation in the hospital all night in order to monitor and investigate their problem. This complete analysis, over a long period of time and including a lot of signals (respiratory signals, ECG, EEG, EOG, EMG, video monitoring, etc) is defined as polysomnogram (PSG). The use of the PSG became more frequently in diagnosing respiratory diseases, but the problem is that the polysomnographic analysis is very expensive. In order to reduce the costs, sleeping laboratories have tried to use only a restricted number of signals to obtain the information about the respiratory problems. E.g., the RR-interval (RRI) analysis of the electrocardiogram (ECG) is a good method to indicate the respiratory problem, because it was shown that some breathing problem affects the heart rate [2, 3].

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Recently, different studies have proved that OSA syndrome is related with the snore [4]. Some groups tried to use the signal collected from the microphone in order to determine the snoring segments, known that there are differences between the snorers with and without OSA [5]. Another signal of interest is the electromyographic signal collected from the chin (EMG Chin) because it is related directly to the respiration process [6]. The problem is that this signal is highly distorted by the snore and must be recovered before application of any analysis.

In our study we used an innovative technique for the analysis of the EMG Chin signal to detect the periods when respiratory disturbances happen.

Recording Technique

The PSG data used in the study were collected at ASKLEPIOS Medical Center and Clinic for Lung diseases, Gauting, Munich, Germany, a hospital specialized in lung diseases.

The following signals were recorded during sleep by the PSG machine: (1, 2) electroencephalogram from brain (EEG 1 — C4/A1, EEG 2 — C3/A2, EEG 3 — C3/C4), (3, 4) electrooculogram from eye movements (EOG Right — F4/A1, EOG Left — F3/A2), (5) position of the body (Bodypos HANDY — F3/A2), (6) electromyogram from the chin muscle (EMG Chin — P4/P3), (7) electrocardiogram (ECG), (8 - 10) the respiratory flow through nose and mouth (Resp Flow Nose Right — Fp2/Cz, Resp Flow Nose Left — Fp1/Cz, Resp Flow Mouth — Fz/Cz), (11, 12) signals from the movement of ribcage and abdomen (Resp Thorax — Thrx, Resp Abdomen — Abdm), (13) sound recorded by a microphone placed above the larynx (Sound raw — Snd), (14) the oxygen saturation, measured by a pulsoxymeter (SAO2 Schwarz Oxi), (15, 16) elctromyogram of the right and left leg (EMG TibialR — T4/T6, EMG TibialL — T3/T5), (17) position of the body (Bodypos Schwarz — Pos), (18) other additional method for measuring breathing with nasal pressure canula (CPAP Schwarz — Prss).

The sampling frequencies for the signals, f_s, are shown in Table 1.

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Table 1: Sampling frequencies of the recorded signals

Channel		Units	f_s
1.	EEG --- C4/A1	µV	125 Hz
2.	EEG --- C3/A2	µV	125 Hz
3.	EOG RIGHT F4/A1	µV	125 Hz
4.	EOG LEFT F3/A2	µV	125 Hz
5.	BODYPOS HANDY F3/A2	"	125 Hz
6.	EMG CHIN P4/P3	µV	250 Hz
7.	ECG --- Ecg	µV	125 Hz
8.	RESP FLOW Fp2/Cz	"	25 Hz
9.	RESP FLOW Fp1/Cz	"	25 Hz
10.	RESP FLOW Fz/Cz	"	25 Hz
11.	RESP THORAX Thrx	µV	25 Hz
12.	RESP ABDOMEN Abdm	µV	25 Hz
13.	SOUND RAW Snd	µV	250 Hz
14.	SAO2 SCHWARZ Oxi	%	25 Hz
15.	EMG TIBIALR T4/T6	µV	250 Hz
16.	EMG TIBIALL T3/T5	µV	250 Hz
17.	BODYPOS SCHWARZ Pos	"	25 Hz
18.	CPAP SCHWARZ Prss	mBar	25 Hz

Wavelet Transform

Wavelet techniques [7] can localize both time and frequency components, as signals are processed and analyzed at various time scales and resolutions. General trends are visible at the lower-resolution scales and high-frequency components are visible at finer, more detailed scales. Basically, the wavelet transform (WT) decomposes a signal onto a set of orthonormal basis functions that all together comprise a wavelet family. Due to the different analyzed signal segment lengths determined by different window sizes of the basis functions, higher frequencies are better resolved in time, and lower frequencies are better resolved in frequency. This means that a certain high frequency component can be better located in time (with less relative error) than a low frequency component. On the contrary, a low frequency component can be better located in frequency compared to high frequency components. Like with other time-frequency approaches such as short-time Fourier transform, time or frequency resolution can be made arbitrarily good with wavelet analysis, but not simultaneously.

Thus, wavelet processing provides good frequency analysis at low frequency and good time resolution at high frequencies. The noise components in a signal can be isolated using detailed resolutions while important high-frequencies transients can be also preserved due to the time localization. Because noise is easily isolated in the wavelet domain, it can be removed while leaving important components almost unaffected.

In digital signal processing, the discrete wavelet transform (DWT) is employed. The result of the DWT is a multilevel decomposition. Wavelet coefficients at detailed high-resolution levels correspond to high frequency signal components, whereas low-resolution levels correspond to low frequency components. Now it is more practical to use filter coefficients rather than actual functions since wavelet functions can rarely be expressed in closed form. The DWT requires two sets of filters. The scaling filter, roughly equivalent to a low-pass filter and denoted as the vector **h**, is computed from a wavelet scaling function. Its coefficients sum to $\sqrt{2}$.

The wavelet filter, roughly equivalent to a high-pass (technically a band-pass) filter and denoted as **g**, is the time-reversed scaling filter with negative alternating coefficients whose sum is zero. The discussion about an orthogonal decomposition of a signal can be extended to non-orthogonal decomposition. Some wavelet can be orthogonal to other wavelets, while not being necessarily orthogonal to their own dilatations and translations. These wavelets are known as bi-orthogonal wavelets. The wavelets generated by low-pass and high-pass decomposition filters are orthogonal to the wavelet generated by the respective reconstruction filters. With a time reversal and alternation of coefficient signs, the low-pass wavelet in the decomposition is the high-pass wavelet in the reconstruction and the high-pass wavelet in the decomposition become the high-pass wavelet in the reconstruction.

The time-scale properties of the discrete wavelet transform are shown in this way: the signal components are localized in time (due to their position in each level) and by scale (roughly corresponding to frequency bands). For a time sequence $\mathbf{x} = [x_0, x_1, ..., x_{n-1}]$, where $n = 2^m$ and m is a positive integer, the corresponding wavelet transform is double indexed. In Table 2, the Wavelet coefficients are described.

Table 2: Wavelet coefficients

w_t^s $0 \le t < 2^{s-1}, 1 \le s \le m$	Scale	Number of elements
w_0^1	1	1
w_0^2, w_1^2	2	2
$w_0^3, w_1^3, w_2^3, w_3^3$	3	4
…	…	…
$w_0^m, w_1^m, ..., w_{2^m-2}^m, w_{2^m-1}^m$	m	2^{m-1}

s is wavelet scale, reflecting the frequency information of the signal, and t is the translation index, indicating the waveform shifting in time. The scale is the inverse of frequency. That is, high scales correspond to low frequencies, and low scales correspond to high frequencies. Consequently, a little peak in the wavelet plot corresponds to the high frequency components in the signal, and a large peak corresponds to low frequency components in the signal. The wavelet spectrum of a spike describes both frequency components and their time location. In that way, waveform matching in the wavelet domain preserves the best properties of matched filter technique in the time and frequency domains.

The discrete wavelet transform provides sufficient information both for analysis and synthesis of the original signal, with a significant reduction in the computation time. It is considerably easier to implement when compared to the continuous wavelet transform [8, 9] and, therefore, it is used in this study with the 2nd order Daubechies wavelet basis; their waveforms have the biphasic feature similar to the EMG components. This type of wavelet basis is also orthogonal and compactly supported.

Results

The EMG Chin signal contains among the disturbing signals (like ECG and vibrations due to the snoring) information that can help in detecting the sleep apnea segments. In Fig. 1, an example of a segment containing sleep apnea is depicted (the respiratory signals are interpolated to get the sampling frequency of 250 Hz).

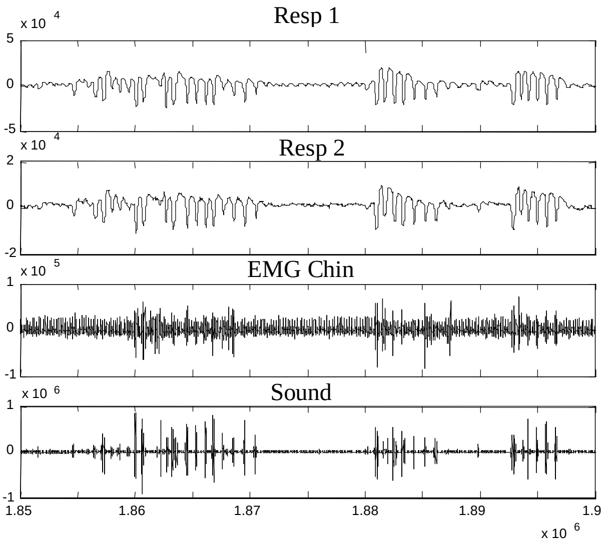

Figure 1: PSG containing apnea segments

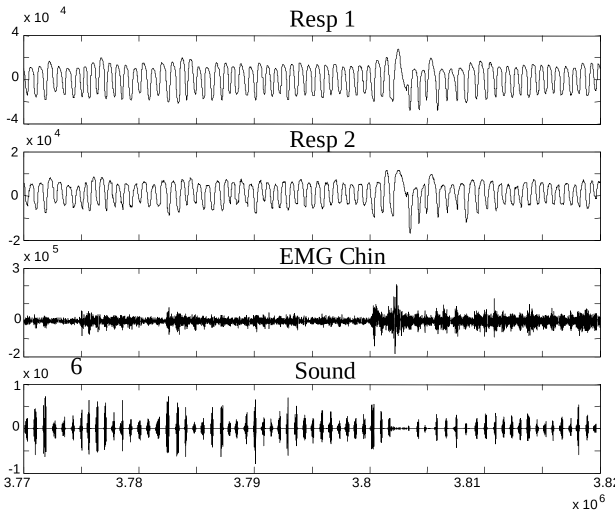

Figure 2: PSG segment disturbed by snore, but with no apnea segments. The problem with the respiration, described by the low amplitude of the respiratory signals, is reflected in the EMG Chin

The high amplitude episodes within the EMG Chin are not only related with the respiratory obstruction but appear also during the snoring episodes, too, usually correlated with low amplitude of the respiratory signals. In order to detect the respiratory problems, thus it is so necessary to identify first the snore segments [10] before analysis of the chin muscle contraction is possible.

In order to identify the muscle contractions in the EMG chin, the first detailed coefficient of the wavelet transform, d_1, is used. Its energy, using a window of 0.4 s, allows the detection of the contraction periods (Fig. 2). For that purpose, the variations of the energy within a window of 0.4 s are analyzed.

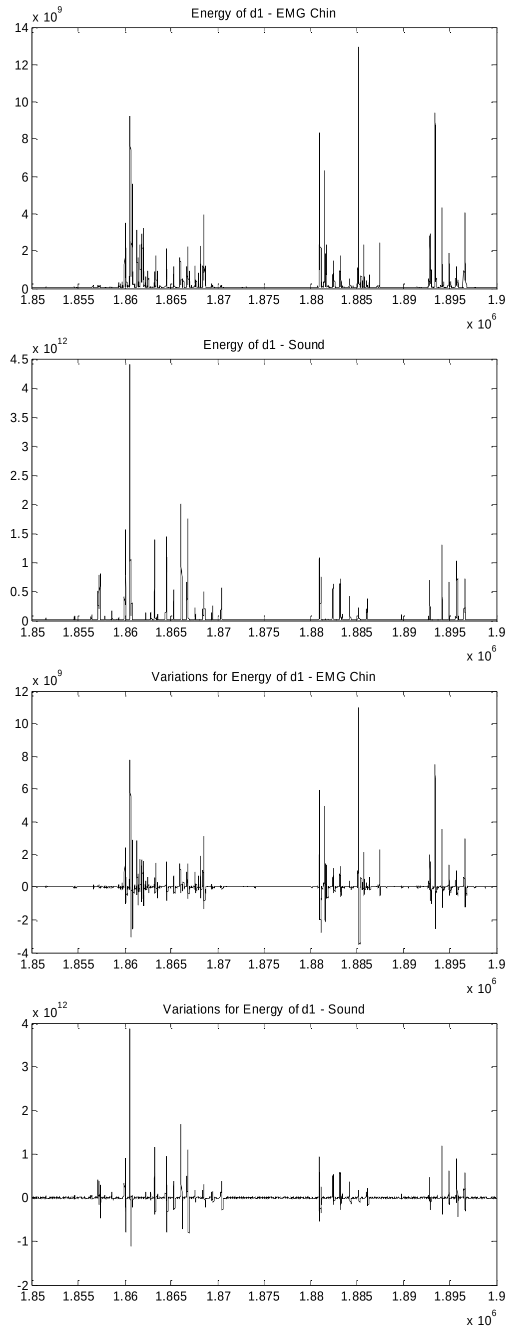

Figure 3: Processing of the PSG containing apnea segments

Discussion

The chin muscle activity related to the snore can be identified by analyzing the correlation between the high frequencies components of the EMG Chin and Sound channels. In our study we have used DWT to isolate the high frequencies [9]. The EMG Chin segments where the chin contracts, undisturbed by the snore, are further analyzed using spectral analysis; they proved to be related with the occurrence of apnea episodes.

The low frequency components extracted from the EMG Chin by use of the DWT correspond to the respiratory activity.

The further study will investigate in more detail the methods to detect the apnea episodes using time-frequency analysis.

Conclusions

The EMG Chin signal can be used to detect the segments when the subjects have respiratory problems over the night, thus it provides an assess to identify the obstructive sleep apnea phases.

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