DETECTION OF SLEEP APNEA/HYPOPNEA EVENTS USING SYNCHROSQUEEZED WAVELET TRANSFORM

Delaram Jarchi[1]*, Saeid Sanei*[2] *and Ales Prochazka*[3]

[1] School of Computing, University of Kent, Kent, UK
[2] School of Science and Technology, Nottingham Trent University, Nottingham, UK
[3]Department of Computing and Control Engineering, University of Chemistry and Technology, Prague

ABSTRACT

In this article, detection of sleep apnea or hypopnea events is addressed using a single channel electrocardiography (ECG) signal by analysis of respiratory extracted modulation. First, R peaks are detected from ECG signal. Then, a time-series with the amplitude (height) and timing of R peaks representing respiratory-induced amplitude modulation is constructed. This signal is resampled evenly at 4Hz. Synchrosqueezed wavelet transform (SSWT) together with an iterative time-frequency ridge estimation is applied to provide a robust estimation of instantaneous respiratory frequency and detect the regions with/without sleep apnea/hypopnea events. Signal reconstruction using inverse synchrosqueezed wavelet transform (ISSWT) has been performed. The appeared peaks can identify and measure the duration of apnea/hypopnea events.

Index Terms— synchrosqueezed wavelet transform, sleep, respiratory rate

1. INTRODUCTION

Obstructive sleep apnea (OSA) is a serious sleep disorder that is characterised as a pause/stop in the breathing pattern. Polysomnography (PSG) as a standard and state of the art system has been used by clinicians in order to detect various sleep disorders including OSA and quality of sleep. The PSG system includes a number of wearable sensing modalities (such as electroencephalography (EEG), electrocardiogram (ECG), sound, and accelerometer) attached to the body and skin to record various signals essential to measure physiological parameters continuously.

The heart signals recorded by the ECG electrodes have been used to identify the OSA events by mainly applying machine learning techniques to classify ECG signal segments into either sleep apnea or non-apnea events[1, 2, 3]. Acoustic signals are also used to classify sleep apnea events [4, 5]. Recently, the accelerometer and the microphone sensors are used to detect sleep apnea using smart phones [6].

In traditional approaches feature extraction is performed from heart rate variability and respiratory signals both derived using ECG signals. Then, machine learning models are trained and tested on the new data. In this paper, instead of fitting models to the trained data, we look in detail into the time-frequency domain of the ECG-derived respiratory modulation to recover and analyse the main respiratory component. We propose to apply a strong time-frequency technique called synchrosqueezed wavelet transform (SSWT) to the 4Hz resampled respiratory induced modulated waveform. The SSWT has provided sharp time-frequency ridges with maximum energy presenting dominant instantaneous respiratory frequencies. In addition, the dominant time-frequency ridge in time domain is reconstructed using inverse synchrosqueezed transform (ISSWT). This signal is then used to directly analyse the ECG signal segments with or without sleep apnea/hypopnea events. The method is expected to provide a new tool for determination of sleep apnea events from photoplethysmography (PPG) signals. The remainder of the paper is as follows. In Section 2, SSWT is explained. The overall method is summarised in Section 3. The results are provided in Section 4. Finally, Section 5 concludes the paper by highlighting its contribution and future work.

2. SYNCHROSQUEEZED WAVELET TRANSFORM

SSWT as a time-frequency reassignment technique to enhance the time-frequency spectral representation of the signal [7], has often been used for analysis of auditory signals. SSWT contains three major steps which are summarised in the following. *Step 1*: In this step, the continuous wavelet transform (CWT) is applied. Suppose that the input signal is $\mathbf{s}$, its CWT is obtained as:

$$W_s(a,b) = \int_{-\infty}^{\infty} s(t) a^{-1/2} \overline{\psi}(\frac{t-b}{a}) dt \qquad (1)$$

where ψ is the selected mother wavelet ($\overline{\psi}$ presents complex conjugate form), t is the time index, a is the wavelet scale, and b is the position parameter. It is necessary to reconstruct the selected mother wavelet to be concentrated on the positive frequency axis; i.e., $\hat{\psi}(\varepsilon) = 0$ for $\varepsilon < 0$. Assume that the input signal is purely harmonic so that it can be presented as $s(t) = A\cos(\omega t)$. Then, using Plancherel's theorem [7], the CWT can be expressed as:

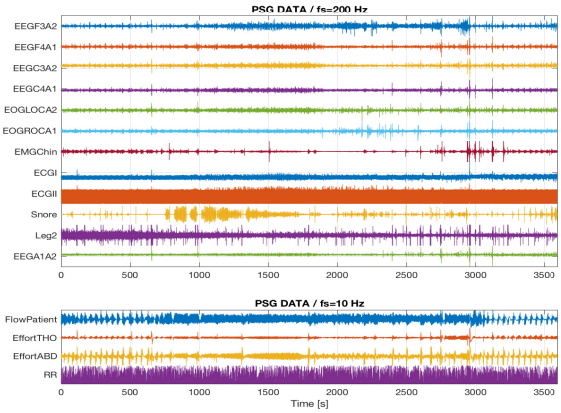

Fig. 1. The signals simultaneously recorded using multiple sensor PSG system [11].

$$
\begin{aligned}
W_s(a,b) &= \int_{-\infty}^{\infty} s(t) a^{-1/2} \overline{\psi}(\frac{t-b}{a}) dt \\
&= \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{s}(\varepsilon) a^{1/2} \overline{\hat{\psi}}(a\varepsilon) e^{ib\varepsilon} d\varepsilon \\
&= \frac{A}{4\pi} \int_{0}^{\infty} [\delta(\varepsilon-\omega)+\delta(\varepsilon+\omega)] a^{1/2} \overline{\hat{\psi}}(a\varepsilon) e^{ib\varepsilon} d\varepsilon \\
&= \frac{A}{4\pi} a^{1/2} \overline{\hat{\psi}}(a\omega) e^{ib\omega}
\end{aligned}
\tag{2}
$$

When $\hat{\psi}(\varepsilon)$ is concentrated around $\varepsilon = \omega_0$, then $W_s(a,b)$ will be concentrated around $a = \omega_0/\omega$ that is spreading out over a region around the horizontal line $a = \omega_0/\omega$. In the case that $\omega = \omega_0/a$ is similar but not exactly equal to the actual instantaneous frequency (IF) of the input signal, then, there exists some non-zero energy for $W_s(a,b)$. The objective of synchrosqueezing is to move all of this energy away from ω. This has been done by reassigning the frequency locations closer to the actual IF. *Step 2*: In this step, the candidate IFs $(\omega(a,b))$ can be calculated by applying the following equation, for which $W_s(a,b) \neq 0$:

$$
\omega(a,b) = -i(W_s(a,b))^{-1} \frac{\partial}{\partial b} W_s(a,b) \tag{3}
$$

It is very straightforward to demonstrate that for a purely harmonic signal $s(t) = A\cos(\omega t)$, $\omega(a,b)$ are obtained as ω [7]. The candidate IFs are used to recover actual frequencies in the next step. *Step 3*: In this step called synchrosqueezing, using $(b,a) \Rightarrow (b,\omega(a,b))$, the time domain is mapped into the time-frequency domain using a re-allocation technique. Considering ω_l as the closest frequency to the original point $\omega(a,b)$, each value of $W_s(a,b)$ is re-allocated into $T_s(\omega_l,b)$:

$$
T_s(\omega_l,b) = (\Delta\omega)^{-1} \sum_{a_k:|\omega(a_k,b)-\omega_l|\leq\frac{\Delta\omega}{2}} W_s(a_k,b) a_k^{-3/2} (\Delta a)_k \tag{4}
$$

where $\Delta\omega$ represents the width of those frequency bins $[\omega_l - \frac{1}{2}\Delta\omega, \omega_l + \frac{1}{2}\Delta\omega]$, $\Delta\omega = \omega_l - \omega_{l-1}$, $(\Delta a)_k = a_k - a_{k-1}$ and $T_s(\omega_l,b)$ is the synchrosqueezed transform at the centres ω_l of successive frequency bins. First, the reassigned frequencies are estimated, at each fixed time point b, using equation (3) for all scales. Then, for each desired IF of ω_l, $T_s(\omega_l,b)$ has been calculated by summing all $W_s(a,b)$ considering the distance between the reassigned frequency $\omega(a,b)$ and ω_l that must be within a specified frequency bin width $(\Delta\omega/2)$.

SSWT can be applied to a desired signal $(s(t))$, where instead of considering $W_s(a,b)$ (equation (1)), we use $T_s(\omega_l,b)$ (equation (4)) to generate the time-frequency spectrum of the input signal for energy analysis. It has been shown in [7] that following the synchronosqueezing stage, the original signal can be analytically reconstructed. In overall, $T_s(\omega_l,b)$ is concentrated more sharply around the actual IFs of the original signal. The resulted spectrum from SSWT is expected to be more sparse than $W_s(a,b)$ obtained by wavelet transform.

For signal reconstruction, ISSWT can be applied which inverts the CWT integrating over the frequencies that are associated with a desired component. Suppose that a fully discretized version of the equation (4) is represented as $\tilde{T}_s(w_l,t_m)$. The input to the ISSWT can be a set of fixed frequency ranges specified by the user, or frequencies obtained by applying a standard least-squares ridge extraction method [8]. Let's denote these frequencies as $l \in L(t_m)$, where $m = 0,...,n-1$, $t_m = t_0 + m\Delta t$, $a_j = 2^{j/n_v}\Delta t$, $j = 1,...,Ln_v$, Ln_v is the number of scales. Then, the signal at mode k can be reconstructed using:

$$
s_k(t_m) = 2R_\psi^{-1} \Re\Big(\sum_{l\in L(t_m)} \tilde{T}_s(w_l,t_m) \Big) \tag{5}
$$

where R_ψ is a normalisation constant defined in [8]. As explained in the next sections, we use both a set of fixed frequencies [0.08-0.5]Hz and those by the least-squares ridge extraction method to retrieve certain respiratory components.

3. METHOD

Detection of normal and abnormal sleep events here relies on the estimated respiratory frequencies. An iterative time-frequency ridge estimation has been provided to find a continuous time-frequency ridge with maximum energy from the SSWT. A disconnection in the time-frequency plane of the SSWT is possibly related to sleep apnea/hypopnea. A pseudocode to reliably estimate the respiratory frequency has been provided in Algorithm 1 which is explained in the following section. Based on Algorithm 1, first, the input ECG signal is processed to locate the R peaks. Then, a time-series containing the timing of the R peaks and their amplitudes (heights) is constructed. This time-series is called amplitude respiratory modulation which is associated with the changes in cardiac output related to the quantity of refill in the vessels at the pe-

riphery [9, 10]. This modulation has been used in various studies to estimate the respiratory rate.

The extracted amplitude modulation signal is evenly resampled at 4Hz. This resampling provides a better resolution for analysis of very low frequency ranges using time-frequency transform ensuring the Nyquist frequency to be well above the highest clinically validated respiratory frequency. Here, we apply the SSWT described in the previous section to provide sharper time-frequency representation than that achieved by the wavelet transform.

For the abnormal sleep patterns specially for OSA patients, there is an episode of discontinuity in the time-frequency plan of the respiratory modulation. As shown in the next section, SSWT has been applied to the original respiratory amplitude modulation (4Hz), and the time-frequency ridge by considering a fixed range of frequencies [0.08 0.5]Hz is estimated. Then, by applying the ISSWT a signal highly correlated with airflow signal is generated (this signal has decreased amplitudes where there is an episode of sleep apnea/hypopnea event). This signal contains significant information that is expected to be retrieved from the PPG signals as an unobtrusive way in future studies to be evaluated against airflow signals. This signal is generated using $ISSWT(\mathbf{W}_{ssw}, [0.08\ 0.5]Hz)$. Here, using Algorithm 1, the time-frequency ridges are estimated using the SSWT iteratively. At each iteration, the number of additional frequency bins [8] is increased by one compared to the previous iteration. In places that there are jumps in the time-frequency ridges, across subsequent iterations, the jumps in frequency are expected to decrease by increasing the number of additional frequency bins. However, after certain iterations, the time-frequency ridges may diverge from the correct one. We have introduced a stopping criterion based on the mean squared error (MSE) between the reconstructed signal modes. The algorithm stops where this error is about to increase. The output of Algorithm 1 is the respiratory frequencies, which

Algorithm 1 Estimation of reliable respiratory frequency

-Input ECG, $c(t) \leftarrow$ input ECG
-Estimate R peaks
-Extract respiratory modulation
$r(t) \leftarrow$ Resample respiratory modulation into 4Hz
-Apply SSWT into 4Hz respiratory modulation
$[\mathbf{W}_{ssw}] = SSWT(r(t))$,
-Iterative frequency ridge estimation at k^{th} iteration
Find time-frequency ridge $[\mathbf{f}_k]$:
$[\mathbf{f}_k] = tfridge(\mathbf{W}_{ssw}, b_k)$, (additional bins $b_k = k$)
Reconstruct signal mode at k^{th} iteration using:
$s_k(t) = ISSWT(\mathbf{W}_{ssw}, \mathbf{f}_k)$
Calculate MSE: $e_k = mean(\mathbf{s}_k - \mathbf{s}_{k-1})^2$
Stop when $e_k > e_{k-1}$
-Reconstruct reliable respiratory frequency [non-zero]:
$[\mathbf{f}_r] = tfridge(SSWT(s_{k-1}(t), [0.08\ 0.5]Hz))$
-Return $t, (\mathbf{f}_r(t) > 0)$

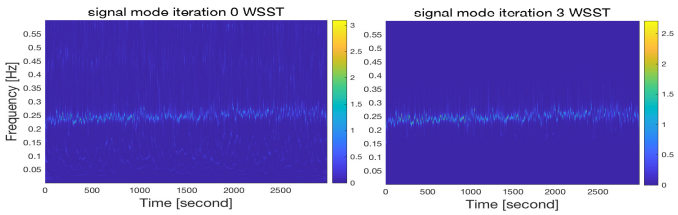

Fig. 2. SSWT of the respiratory modulation (4Hz) at iteration 0 and iteration 3. SSWT is more smooth at iteration 3.

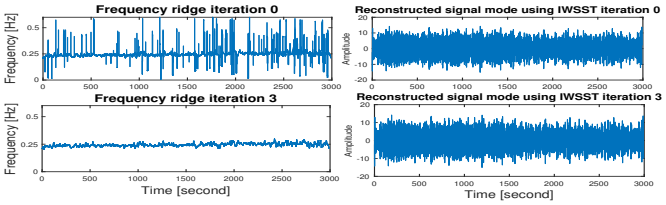

Fig. 3. Frequency ridges estimated at iterations 0 and 3.

are nonzero for segments of the data with normal sleep patterns. However, it returns zero for segments of the data where abnormal sleep patterns exist. Therefore, we are able to focus on segments of the data with zero respiratory rate and try to recover information regarding the abnormal sleep events. Here, we have reconstructed a signal mode which the signal is zero in segments of the data with abnormal sleep events from Algorithm 1 using $ISSWT(\mathbf{W}_{ssw_{k-1}}, [0.08\ 0.5]Hz)$ where $\mathbf{W}_{ssw_{k-1}} = SSWT(s_{k-1}(t))$. If from this signal we subtract the original filtered 4Hz respiratory modulation, the residual signal will be around zero at segments of valid/normal respiratory frequency while the signal pulse peaks with higher amplitudes corresponding to the sleep apnea/hypopnea events. This is due to the fact that we can correctly reconstruct a signal in time-domain for normal respiratory frequencies with almost zero discontinuity.

4. RESULTS

The recorded PSG signals include an EEG, ECG, electro-oculogram (EOG), electromyogram (EMG), breathing (flow) that provides the airflow signal, respiratory effort channels, sound and movement sensors. The dataset used in this research included a set of healthy subjects and patients with

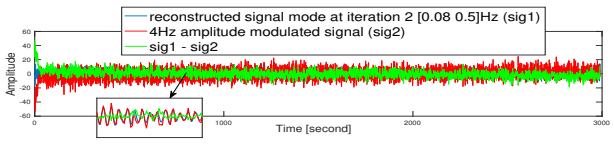

Fig. 4. Reconstructed signal mode at iteration 3, original amplitude modulated signal (4Hz), and residual are overlaid.

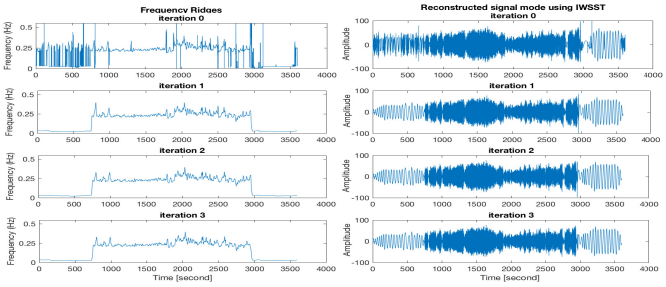

Fig. 5. The frequency ridges at 3 iterations are shown. The algorithm is stopped at iteration 3.

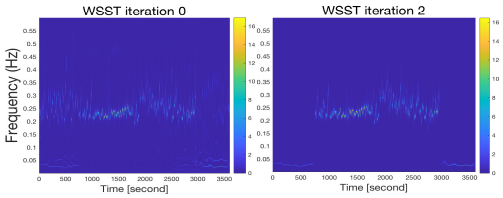

Fig. 6. SSWT of the respiratory modulation (4Hz) at iteration 0 and iteration 2. SSWT is more smooth at iteration 2 for segments where there are no evident apnea/hypopnea events.

OSA [11]. Sample signals from a PSG system for patient with OSA are shown in Fig. 1. One ECG channel (ECGI) was used to estimate and evaluate the respiratory frequencies. The sampling frequency of ECG signal was fixed at 200Hz while the airflow signal was sampled at 10Hz.

A healthy subject was selected and Algorithm 1 applied to reconstruct the frequency ridge component representing the respiratory frequency. The calculated MSE at iterations 1,2,3 and 4 were obtained as 1.2, 0.04, 1.6×10^{-4} and 2.7×10^{-4}. The algorithm stopped at iteration 4, therefore, the frequency ridge and signal mode at iteration 3 were reconstructed. The SSWT of the original respiratory modulation (4Hz) (called iteration 0) and the reconstructed signal mode at iteration 3 are shown in Fig. 2. The frequency ridge and reconstructed signal mode are shown in Fig. 3. As seen in this figure, there are a significant number of frequency jumps at iteration 0 where there is no additional frequency bins (zero additional frequency bin) while the frequency jumps are minimised at iteration 3. If we apply the ISSWT to the SSWT obtained by the signal mode at iteration 3, (with frequencies

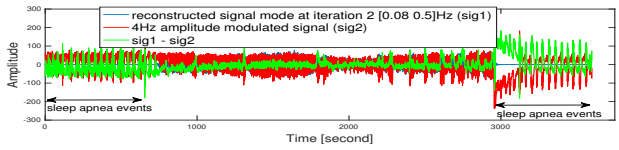

Fig. 7. Reconstructed signal mode at iteration 3, original amplitude modulated signal (4Hz) and residual are overlaid.

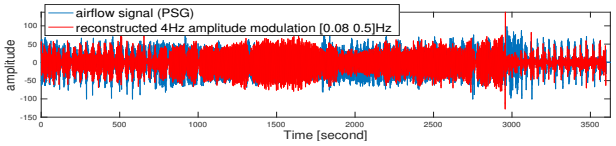

Fig. 8. Reconstructed signal mode from [0.08 0.5]Hz frequencies (ISSWT) with a high correlation to airflow signal.

[0.08 0.5]Hz), the reconstructed signal is highly correlated with the original respiratory modulation (4Hz). These two signals along their residual signal are plotted in Fig. 4. In the following it is shown how this residual signal is useful in identification of abnormal sleep events noting that the data from a healthy subject was used in Fig. 4. Algorithm 1 was applied to the input ECG signal of a patient with OSA. The calculated MSE at iterations 1,2 and 3 were obtained as 168.6, 2.7, and 8.7. The algorithm stopped at iteration 3, therefore, the frequency ridge and signal mode at iteration 2 were reconstructed. The results of frequency ridge extraction and signal mode reconstruction are shown in Fig. 5 at iterations 0, 1, 2 and 3 which represent 0, 1, 2 and 3 additional frequency bins, respectively. SSWT of the reconstructed component at iterations 0 and 2 are shown in Fig. 6 where the respiratory frequencies within [0.08 0.5]Hz are removed from the beginning and end of the signal at iteration 2 which correspond to sleep apnea/hypopnea events. If we apply the ISSWT as suggested in Algorithm 1, only respiratory frequencies for non-apnea/hypopnea events are non-zero and the rest is zero. The corresponding time-domain reconstructed signal is also zero for apnea/hypopnea events. From this signal (obtained by applying ISSWT at iteraion 2) the original respiratory modulation (4Hz) is subtracted. The residual plotted in Fig. 7 (green) is zero for non-apnea/hypopnea events. From this figure, the pulse peaks have appeared in the residual signal which can be used both to identify and measure the duration of sleep apnea/hypopnea events. In addition, ISSWT applied to the original respiratory modulation (4Hz) using [0.08 0.5]Hz shown in Fig. 8 is highly correlated with the airflow signal.

5. CONCLUSIONS

This paper has directly evaluated the spectrum of respiratory induced modulation of ECG from PSG recordings to investigate the sleep apnea/hypopnea events. Unlike previous methods that use feature extraction and machine learning techniques for this purpose, we have provided signal processing techniques to observe changes in spectrum of the ECG respiratory modulation to identify abnormal sleep events. In future studies, the method will be applied to the PPG signals to estimate these abnormal sleep events as well as designing a reliability index for breathing rate estimation that has been done in this paper by iterative frequency ridge estimation technique to detect and measure duration of sleep apnea/hypopnea events.

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