Derivation of Respiratory Effort from Photoplethysmography

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***Abstract*—In this paper, a new and non-invasive method has been proposed to retrieve respiratory effort component from photoplethysmography (PPG) sensor. The PPG signals are recorded using a commercial wrist worn device. Inverse synchrosqueezed wavelet (ISSW) transform has been applied to reconstruct the respiratory component and then to derive respiratory effort component. The reconstructed respiratory component and the respiratory effort signal from PPG are shown to be highly correlated with airflow signal and extracted respiratory effort obtained using a thermocouple secured under nose. The findings in this paper can make significant changes in various applications such as for sleep analysis, where continuous monitoring of respiratory effort from a wrist worn sensor unobtrusively is crucial for identification of various sleep abnormalities such as sleep apnea.**

***Index Terms*—respiratory, inverse synchrosqueezed wavelet transform, PPG**

I. Introduction

Recently there has been an increasing amount of research studies on estimation of respiratory rate, i.e. breathing rate, from wearable sensors based on photoplethysmography (PPG) or electrocardiography (ECG) [1]. In most of research studies, estimation of respiratory rate has been performed by considering average number of breaths using overlapped/non-overlapped windowed signals by applying various techniques such as time-frequency spectral analysis. Estimation of instantaneous respiratory rate has been addressed in few studies [2] using synchrosqueezed wavelet transform (SSWT) [3], [4]. Estimation of respiratory effort, which is an important clinical parameter, has been much less investigated. It can provide useful information for certain applications such as sleep analysis.

There is a recent pilot study in [5] where the candidate feature parameters are extracted from various respiratory derived modulations using PPG. The PPG signals and airway pressure signals as reference using a facemask consisting of a pneumotach containing a number of interchangeable flow resistors are recorded. The subjects are asked to breath with a consistent effort (less effort or more effort). A regression model has been applied to identify whether there exists a positive relationship between respiratory effort parameters extracted from PPG and airway pressures. The results suggested that there is a monotonic relationship between several PPG based parameters and airway pressure. Overall, extracting various time-domain features from PPG signals [5]–[7] to estimate respiratory effort can be a challenging task for a wide range of subjects.

In this work, we introduce a detailed spectral analysis of the respiratory component derived from PPG. The respiratory component is reconstructed using inverse synchrosqueezed wavelet transform (ISSWT). Then, from peak amplitudes of the reconstructed respiratory component, a respiratory effort component is derived. This signal has shown to be highly correlated with the constructed respiratory effort component from peak amplitudes of the airflow signal produced by the thermocouple.

The remainder of the paper is as follows. In Section II, the SSWT and ISSWT are briefly described. The method to estimate respiratory rate, respiratory component and respiratory effort is explained in Section III. Section IV covers the results of applying the proposed method to the recorded PPG signals compared with thermocouple using five healthy subjects. Finally, section V concludes the paper by highlighting the main contribution of the paper and potential future applications.

II. Synchrosqueezed Wavelet Transform

SSWT is a two-stage technique where the time-frequency transform of the input signal is constructed in the first stage, then, a reassignement technique is applied to the time-frequency spectrum in the second stage [3], [4]. The objective of the SSWT is to enhance the time-frequency spectral representation of the input signal. SSWT has been first applied for auditory signal analysis [3]. *Stage 1*: The continuous wavelet transform (CWT) is applied to the input signal in Stage 1. Consider the CWT of input signal $\mathbf{s}$ 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), a is the wavelet scale, t is the time index, and b is the position parameter. One necessary condition for the mother wavelet is that it must be concentrated within the positive frequency range; i.e., $\hat{\psi}(\varepsilon) = 0$ for $\varepsilon < 0$. In order to understand the basic operation of the SSWT, suppose a purely harmonic signal as the input to the SSWT algorithm. This

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signal can be presented as $s(t) = A\cos(\omega t)$. Based on the Plancherel's theorem [3], the CWT can be formulated as:

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

Since $\hat{\psi}(\varepsilon)$ is concentrated around $\varepsilon = \omega_0$, then $W_s(a,b)$ is concentrated around $a = \omega_0/\omega$, and will be spreading out over a region of the horizontal line a:

$$W_s(a,b) = \frac{A}{4\pi} a^{1/2} \overline{\hat{\psi}}(a\omega) e^{ib\omega} \tag{3}$$

Consider a situation that $\omega = \omega_0/a$ is alike but not exactly identical to the actual instantaneous frequency (IF) of the input signal, then, there exists some non-zero energy for $W_s(a,b)$. The basic idea behind synchrosqueezing is to propose a method to move all of this energy away from ω. The method used in SSWT is to reassign the frequency locations closer to the actual IF to produce an enhanced time-frequency spectral representation. *Stage 2*: In this stage, first the the candidate IFs ($\omega(a,b)$) are calculated for which $W_s(a,b) \neq 0$, using the following equation:

$$\omega(a,b) = -i(W_s(a,b))^{-1} \frac{\partial}{\partial b} W_s(a,b) \tag{4}$$

Having a purely harmonic signal $s(t) = A\cos(\omega t)$, it is straightforward to demonstrate that $\omega(a,b)$ are derived as ω [3]. In order to recover actual frequencies, the candidate IFs are used. In the synchrosqueezing step (using $(b,a) \Rightarrow (b, \omega(a,b))$), the time domain is mapped into the time-frequency domain by applying a re-allocation technique. Each value of $W_s(a,b)$ is re-allocated into $T_s(\omega_l, b)$, using ω_l as the nearest frequency to the original point $\omega(a,b)$:

$$T_s(\omega_l, b) = (\Delta\omega)^{-1} \sum_{a_k : |\omega(a_k,b) - \omega_l| \leq \frac{\Delta\omega}{2}} W_s(a_k, b) a_k^{-3/2} (\Delta a)_k \tag{5}$$

where $\Delta\omega$ is 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 sequential frequency bins. At each fixed time point b, using equation (4), the reassigned frequencies are estimated for all scales. Then, for each desired IF of ω_l, $T_s(\omega_l, b)$ has been calculated. This has been done by summing all $W_s(a,b)$ taking into account the distance between the reassigned frequency $\omega(a,b)$ and ω_l which must be within a specified frequency bin width ($\Delta\omega/2$).

ISSWT: To obtain the time-frequency spectrum of a desired input signal ($s(t)$) by SSWT, $T_s(\omega_l, b)$ must be calculated using equation (5). One advantage in using SSWT is that as shown in [3] following the synchronosqueezing step, 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 (equation 5). Therefore, the spectrum given by the SSWT is expected to be more sparse than $W_s(a,b)$ produced by wavelet transform (equation 1).

ISSWT can be applied for signal reconstruction. It inverts the CWT integrating over the frequencies that are associated with a desired component. Consider a fully discretized version of equation (5) which is represented as $\tilde{T}_s(w_l, t_m)$. A set of fixed frequency ranges specified by the user can be used as the input to the ISSWT. Alternatively, these frequencies can be 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. Therefore, given the frequencies of a desired component (k^{th}), the corresponding signal can be reconstructed using:

$$r_k(t_m) = 2R_\psi^{-1} \Re(\sum_{l \in L(t_m)} \tilde{T}_s(w_l, t_m)) \tag{6}$$

where R_ψ is a normalisation constant defined in [8].

III. Method

The main motivation for this research is to use maximum-energy time-frequency ridge from spectrum of the respiratory modulation to estimate the respiratory component and derive the respiratory effort. Here, the time-frequency ridge has been estimated from the spectrum produced by applying SSWT. First, respiratory modulation needs to be estimated from the PPG signals. There are three respiratory modulations including amplitude, intensity and frequency modulations [1]. Both amplitude and frequency respiratory modulations have been successfully applied to our dataset to produce the respiratory component for reliable estimation of respiratory rate in breaths per minute (bpm). Once, the respiratory modulation is constructed, it is resampled into a 4Hz signal as suggested in various studies [2]. The time-frequency spectrum of the resampled signal has been obtained using the SSWT method for further analysis to derive the respiratory effort as detailed in the following and summarised in Algorithm 1.

Algorithm 1 Estimation of Respiratory Effort

-Input PPG; $s(t) \leftarrow$ input PPG
-Estimate pulse peaks
-Extract respiratory modulation
  $r_m(t) \leftarrow$ Resample respiratory modulation into 4Hz
-Apply SSWT into 4Hz respiratory modulation
  $[\mathbf{W}_{ssw}] = SSWT(r_m(t))$,
  Find time-frequency ridge indices, set penalty: p
  $[\mathbf{i}_{ridge}] = tfridge(\mathbf{W}_{ssw}, p)$,
  Reconstruct respiratory component using:
  $r_c(t) = ISSWT(\mathbf{W}_{ssw}, \mathbf{i}_{ridge})$,
  Detect peaks of $r_c(t)$,
  Form a time-series ($r_f(t)$) from the peak amplitudes
-Return respiratory effort $r_f(t)$

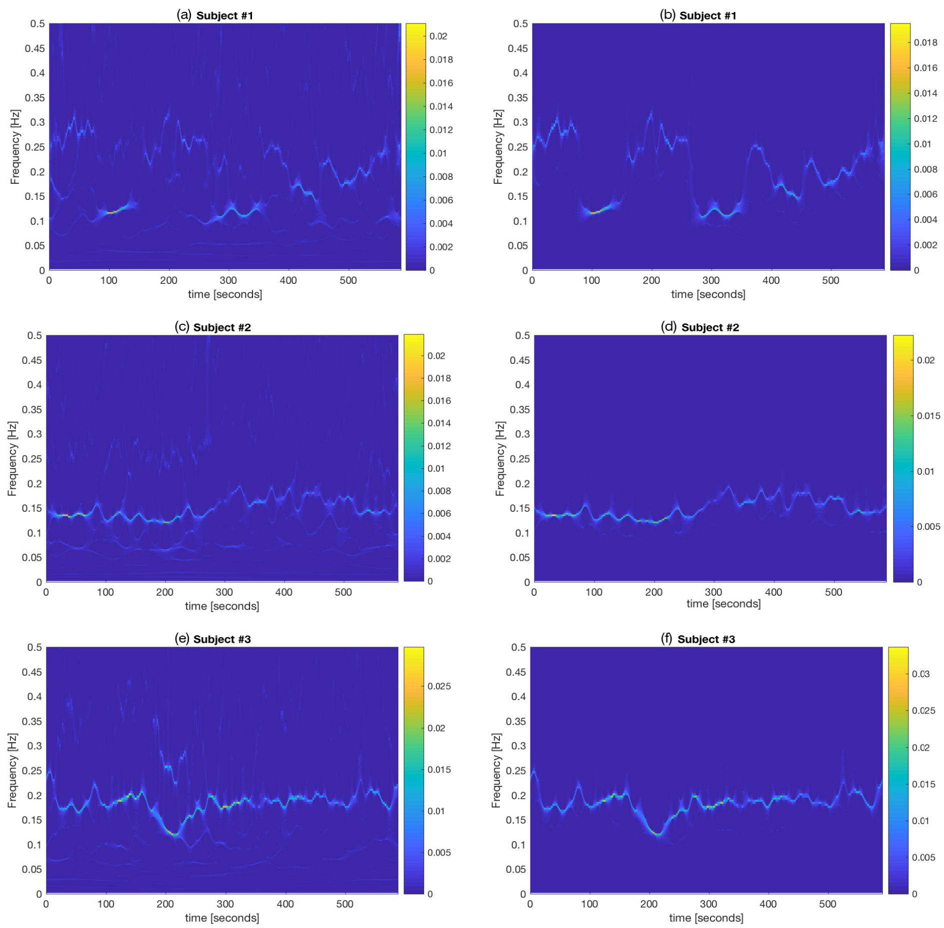

Fig. 1. (a,c,e) Original spectrum by applying SSWT to the extracted 4Hz respiratory modulation. (b,d,f) Enhanced spectrum by applying SSWT to the extracted respiratory component (obtained by applying ISSW using the estimated high-energy time-frequency ridge).

IV. Results

The selected dataset includes a set of five healthy subjects wearing the sensor from WaveletHealth Inc. (Mountain view, CA, USA) to generate the PPG signals and a thermocouple secured under as reference. The thermocouple was able to detect the warm air flowing out of the nostrils at each expiration. Therefore, the airflow signal contained one pulse for each breath. The subjects were sitting comfortably in an armchair. They were asked to have one or more deep breaths in order to induce some variations in respiratory rate and also respiratory effort. The experiment lasted for almost 10 minutes.

The infrared PPG signals recorded from the WaveletHealth sensor were used to derive respiratory effort component. The PPG signals are first processed where the pulse peaks are located. Using the detected pulse peaks, the respiratory modulation (frequency modulation) has been estimated. This modulation has been resampled to a 4Hz signal. Then, the SSWT has been applied to the resulted respiratory modulation to produce the time-frequency spectrum. This spectrum can be used to estimate respiratory frequency and then present it in the form of respiratory rate (bpm). Since this spectrum can include sparse time-frequency bins with high-energy not related to breathing, accurate estimation of the respiratory spectral component is not always very straightforward. To min-

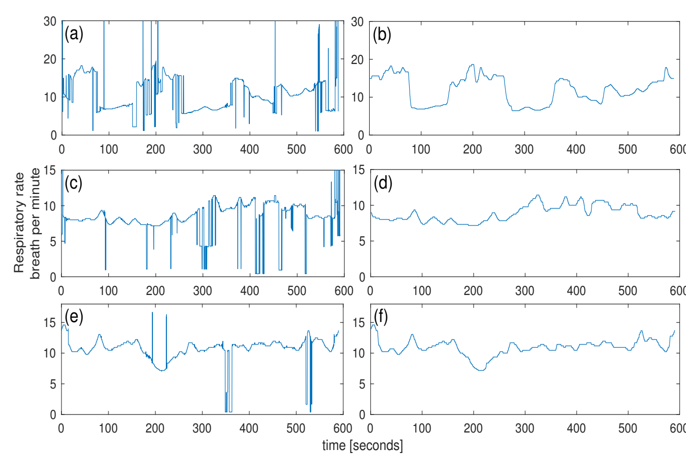

Fig. 2. Estimated respiratory rate using a penalty value equal to 0 (a,c,e) and 2 (b,d,f) for subjects #1 (a,b), #2 (c,d) and #3 (e,f). A smoother respiratory rate has been obtained by increasing the penalty value.

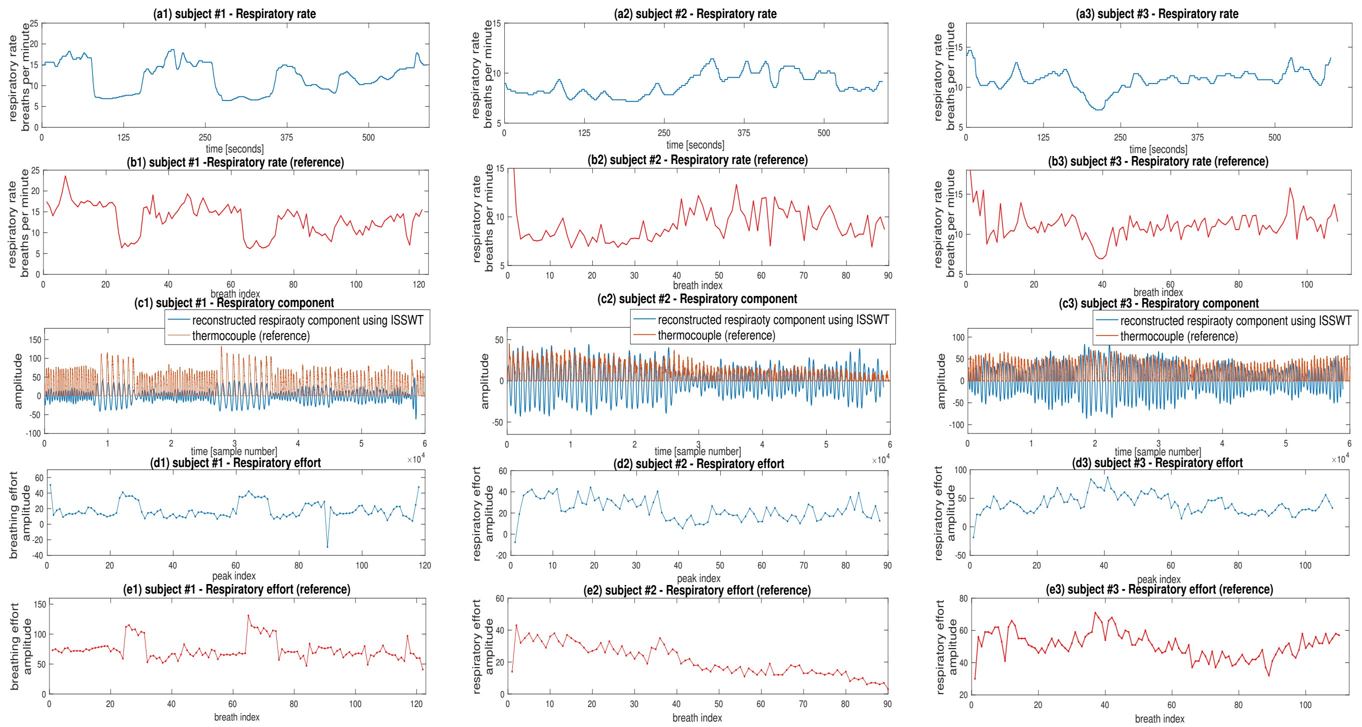

Fig. 3. Estimated respiratory rate, respiratory component and respiratory effort using the proposed method (using PPG) versus reference (using thermocouple) for three subjects #1 (a1,b1,c1,d1,e1), #2 (a2,b2,c2,d2,e2) and #3 (a3,b3,c3,d3,e3).

imise the effect of such bins which can make the estimation of respiratory rate less accurate, usually overlapped moving windows are formed to estimate the average respiratory rate. In a recent study in [2], a time-frequency mask using average respiratory rate has been applied to the resulted SSWT spectrum to extract instantaneous respiratory rate (IRR). The IRRs provide more information than average RRs. Although the focus in this study is not on estimation of IRRs, enhancing the spectrum of the respiratory modulation given by the SSWT can help both improvement of estimated IRRs and derivation of the respiratory effort. A time-frequency ridge method has been applied based on [8] using a standard least-squares ridge extraction to find the frequencies of the desired respiratory component which span a high energy in the SSWT spectrum. In places that there are frequency jumps along the time-frequency ridge, a higher value (0 refers to no penalty) for penalty variable is used. The penalty has been incorporated into the ridge estimation method to penalises changes or jumps in frequencies [8].

In Fig. 1(a,c,e), the original spectrum of the extracted respiratory modulations are shown for three subjects (#1,#2 and #3). In Fig. 1(b,d,f), the corresponding SSWT of the reconstructed signals after finding the maximum-energy time-frequency ridge (penalty=2, see Algorithm 1) are provided. As it can be seen from Fig. 1, that the SSWT spectrum is enhanced using the time-frequency ridge estimation and a non-zero penalty value (2). It has been shown in Fig. 2(a,c,d) that a penalty value equal to zero, provides a noisy estimate of respiratory frequency (and consequently respiratory rate). After setting the value of the penalty variable to 2, less noisy estimates of the respiratory frequencies are obtained using the time-frequency ridge extraction method. Finally, after extraction of the maximum high-energy time-

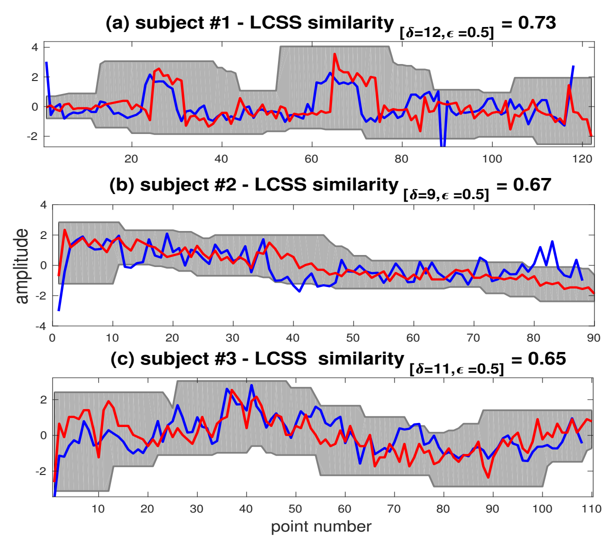

Fig. 4. Similarity of derived respiratory effort component by applying the proposed method to the PPGs (WaveletHealth sensor) and airflow signals (from thermocouple) for three subjects #1(a), #2(b) and #3(c). For each plot, red curve corresponds to the extracted respiratory rate from thermocouple, while blue curve corresponds to the derived respiratory effort component from PPG.

frequency ridge, the obtained frequencies (and their locations using ridge estimation method) are used to invert the original SSWT transform. The resulted respiratory component using the ISSWT has shown to be highly correlated with the airflow signal recorded using the thermocouple. Then, the signal peaks are located on the resulted respiratory component and their amplitudes are used to construct a new time-series. This signal has been considered as respiratory effort component having a very good agreement with the time-series of peak amplitudes of the airflow signal. This follows the pseudocode of the algorithm for estimation of respiratory effort signal component as shown in Algorithm 1.

The thermocouple signals are used as reference to compare the estimated respiratory rate, respiratory component and respiratory effort. The timings and amplitudes of peaks on the airflow signals presenting each individual breath (from thermocouple) are used to estimate respiratory rate and respiratory effort, respectively. On the other hand, for the proposed method using the input PPG signals, the estimated frequencies from SSWT using time-frequency ridge method are used to estimate respiratory rate, while the reconstructed signal using ISSW is used to produce the respiratory component (similar to the airflow signal). Finally, the peak amplitudes of the constructed respiratory component are used to derive respiratory effort.

In Fig. 3, the estimated respiratory rate, derived respiratory component and respiratory effort versus the reference signals are shown for three subjects (subject #1, #2 and #3). The similarity of derived respiratory effort using the proposed algorithm and the reference (from the peak amplitudes of the thermocouple signal) is provided in Fig. 4 for three subjects using the longest common subsequence algorithm (LCSS) [9], [10]. For the other two subjects the similarities of 0.50 and 0.36 were obtained. The reason for using LCSS for similarity measurements, is the difference in the number of samples. The airflow signals produce respiratory effort component where the samples are related to detected peaks (one sample per breath), while the proposed method is based on a uniform 4Hz signal (one created sample is related to 0.25 seconds in time).

V. Discussion and conclusion

Estimation of respiratory rate using time-frequency spectrum or feature based methods has been widely studied recently. However, they lack estimation of respiratory effort directly through analysis of the spectrum of respiratory modulation. This paper has validated derivation of respiratory effort from PPG signals by enhancing the time-frequency spectrum (using SSWT) of the respiratory modulation. The results are quite promising where large scale data collection in future studies is recommended to validate derivation of respiratory effort for patients. More specifically, the proposed method can have a big impact on sleep analysis applications mainly to identify the abnormalities in the sleep signals such as sleep apnea by direct examination of time-frequency spectrum using the SSWT and signal reconstruction using ISSWT.

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