EXTRACTION OF RESPIRATORY ACTIVITY FROM PULSE OXIMETER SIGNALS USING TUNABLE Q-FACTOR WAVELET TRANSFORM

K. Venu Madhav

Department of E&I Engineering,
Kakatiya Institute of Technology & Science, Warangal, India

ABSTRACT

Online monitoring of respiratory activity is essential in situations such as cardiopulmonary disorders, ambulatory monitoring, stress tests, sleep disorder investigations and post-operative hypoxemia. Extraction of respiratory activity from physiological signals having respiratory influence such as pulse oximeter's photoplethysmographic (PPG) signals would be an alternative under clinical settings compared to that of all direct methods of recording respiratory signals such as spirometry, pneumography or capnography. The respiratory information can be extracted from PPG signal using a simple band pass filter, but the design of narrow band pass filter (NBPF) with classical filter design cannot be possible. In this paper, we present a simple method, based on tunable Q-factor Wavelet transform (TQWT), for extraction of respiratory activity from PPG signals. Advantage of TQWT stems from the fact that, the realization of practical narrow band pass filter with a specific Q-factor value can be designed, which motivated the authors to use for this application. The method is applied on, PPG data recorded from 15 healthy subjects; each consisting of simultaneously recorded PPG and respiratory signals. The extracted respiratory signals are compared with the original respiratory signals. Statistical parameters such as relative correlation co-efficient (RCC) in time domain as well as magnitude squared coherence (MSC) in frequency domain are used for performance evaluation along with error analysis using the accuracy rate (AcR) and normalized mean square error (NRMSE). Experimental results have shown a good acceptance for the extracted signal when compared with the originally recorded respiratory signal. The proposed technique could become an efficient approach for extraction of surrogate respiratory activity from PPG signals, avoiding usage of additional specialized sensor for respiratory monitoring.

KEYWORDS

PPG, respiratory signal, Wavelet Transform, Tunable Q-factor.

1. INTRODUCTION

Respiration rate is traditionally obtained making use of cumbersome devices or techniques, like spirometry, pneumography, respiration inductance plethysmography (RIP), using strain gauges or piezoelectric transducer devices strapped to chest or abdomen, or pressure transducers to measure nasal air pressure, which may in general interfere with natural breathing and are less well tolerated by the patients under clinical settings. Electrocardiogram (ECG) and pulse oximeter's photoplethysmogram (PPG) are the two vital electrophysiological signals cautiously monitored by clinicians during anaesthesia, post-operative and intensive care. Respiratory monitoring in the clinical setting is challenging and no golden standard exists. Hence, extracting surrogate respiratory information from electrophysiological signals having respiratory influence is of research interest and is increasingly being used in clinical practice.

A. Respiratory induced modulations in physiological signals

ECG is a widely accepted diagnosis tool in clinical validations of heart related diseases. The effect of respiration-induced heart displacement on the ECG was first studied by Einthoven et al [1] and quantified further in [2], [3]. It has been experimentally shown that the ECG has variations in amplitude and frequency with reference to respiration [4]-[5].

Pulse oximeters provide non-invasive continuous monitoring of arterial blood oxygen saturation making use of PPG signals [6]. PPG signal is composite in nature and has five different frequency components in the interval 0.007–1.5 Hz [7], sources of these frequency components may be due to respiration, blood pressure control, thermoregulation, autonomous nervous system (ANS) and heart synchronous pulse waveform. The AC component of PPG signal is synchronous with the heartbeat. In addition to heart-synchronous variations, the PPG signal contains respiratory-induced intensity variations (RIIV) [8]-[10] and found a correlation in the amplitudes of RIIV in the PPG and respiratory variations in peripheral venous pressure. This modulation arises from respiratory-induced variations in venous return to the heart, caused by the alterations in intrathoracic pressure. The following is a brief literature related to signal specific respiratory extraction algorithms.

B. PPG derived respiration (PDR) algorithms

A PPG signal consists not only the heartbeat component but also a respiratory information. A digital filtering technique [11] was used to extract respiratory signal from the PPG signal wherein the low pass filter characteristics must be adaptive in nature to allow all possible frequencies corresponding to different levels of respiratory frequencies. Several other initial efforts in the direction of extraction of respiratory information include [12]-[13]. While time-frequency analysis in wavelet space clearly allowed accurate detection on individual breaths from PPG signal, a fully automated algorithm based on secondary wavelet feature decoupling [14] received much attention and resulted in accurate measurement of respiratory rate from PPG signals. A bivariate AR model [15] demonstrated a high coherence between respiration signal and PPG. A very recent significant and exhaustive work carried out by [16]-[18] provided best results to estimate respiratory rate from pulse oximeter signal include a time-frequency spectral estimation method called variable frequency complex demodulation (VFCDM) and modified multiscale PCA (MMSPCA).

2. METHOD

A. Review of Tunable Q-factor Wavelet Transform (TQWT):

Recently, Selesnick (2011) introduced a multi-resolution analysis toolbox, in which the Q-factor is easily adjustable [19]. The transform can be tuned according to the oscillatory behavior of the signal to which it is applied. The Q-factor of a given wavelet is a measure of the wavelets central frequency to bandwidth ratio, and controls the oscillatory behavior of the wavelet. The tunable Q-factor wavelet transform is a discrete-time wavelet transform, in which the usual wavelet variables of position (time) and scale (frequency sub-band) are considered, along with an additional variable of Q-factor (central frequency to bandwidth ratio of wavelets). Constant Q signal analysis and synthesis gives a much more clear information of a signal of interest. Wavelet transforms (constant-Q transforms) with low Q-factors are useful for the efficient representation of piecewise smooth signals whereas wavelet transforms with high Q-factors are useful for the efficient representation of oscillatory signals such as an audio signal or an electro encephalogram (EEG) rhythm.
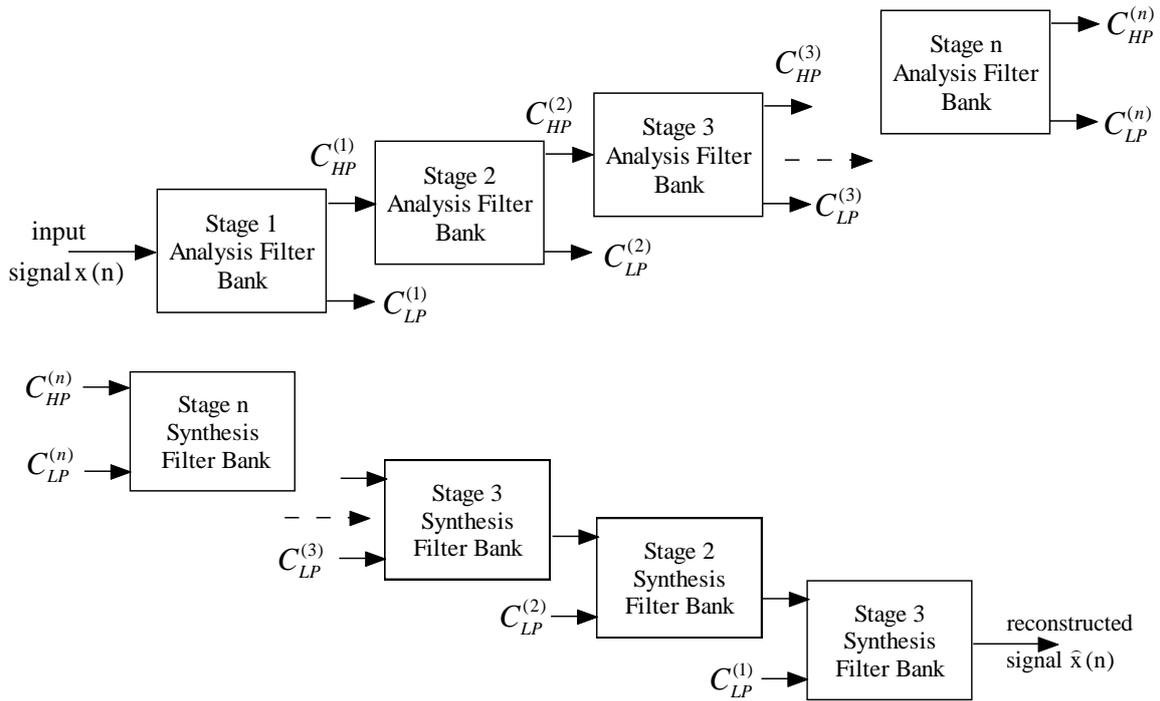
Figure 1. Decomposition and reconstruction stages for Tunable Q-factor Wavelet Transform (TQWT)

The decomposition and reconstruction structure of TQWT is shown in Fig. 1. The concerned analysis and synthesis filter bank structures are shown in Fig.2 and Fig.3 respectively. Important building blocks of analysis, synthesis filter banks are low pass scaling (LPS) and high pass scaling (HPS).
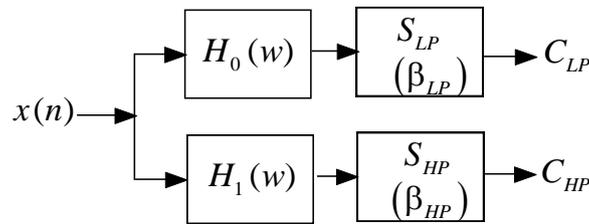
Figure 2. Analysis filter bank of TQWT
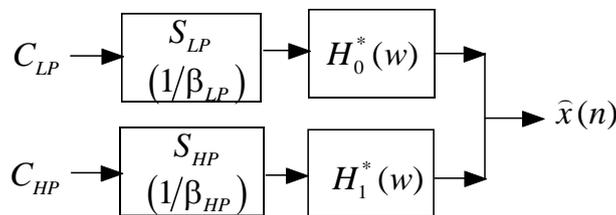
Figure 3. Synthesis filter bank of TQWT

The LPS refers to frequency domain scaling which preserves low frequency information. The output of the LPS will have a sampling frequency of $\beta_{LP} F_s$, where Fs is the sampling rate of the input signal. The HPS refers to frequency domain scaling which preserves high frequency

information around Nyquist frequency $(w=\pi)$. The low pass scaling factor β_{LP} and high pass scaling factor β_{HP} may be greater than 1 or less than 1. The LPS signal C_{LP} and the HPS signal C_{HP} having sampling rates $\beta_{LP} F_S$ and $\beta_{LP} F_S$ respectively. The scaling parameters are chosen such a way that the wavelet transform will not overly redundant.

$$0 < \beta_{LP} < 1;\ 0 < \beta_{HP} < 1;\ \beta_{LP} + \beta_{HP} > 1 \tag{1}$$

The nth level band pass filter center frequency, bandwidth and Q-factor can be given as

$$f_c = \left(\beta_{LP}\right)^n \left(\frac{2 - \beta_{HP}}{4\beta_{LP}}\right) F_S \tag{2}$$

$$BW = \frac{1}{2}\, \beta_{HP} \left(\beta_{LP}\right)^{n-1} F_S \tag{3}$$

$$Q = \frac{w_c}{BW} = \left(\frac{2 - \beta_{HP}}{\beta_{HP}}\right) \tag{4}$$

So the scaling factors can be chosen from desired Q-factor and redundancy as

$$\beta_{HP} = \frac{2}{Q+1};\ \beta_{LP} = \left(1 - \frac{\beta_{HP}}{r}\right) \tag{5}$$

3. MATERIALS

A. *Experimental setup for data acquisition*

For acquiring PPG and reference respiratory signals, simultaneously from various subjects an experimental setup was designed and developed in the laboratory. The PPG setup consisting of a clip-on type PPG sensor (Nellcor N100), housing an IR (940nm) and Red (660nm) LEDs on one side and a matched photodiode detector on the other side, is to be attachedto the index finger of the subject as shown in Fig.4.The output of the analog circuit was interfaced to a computing system using National Instruments (NI), data acquisition card NI-DAQPad-6009 having a 12-bit resolution. Suitable virtual instrumentation (VI) programs were developed to acquire and record the signals at a sampling frequency of 1000Hz, under LabVIEW virtual environment.
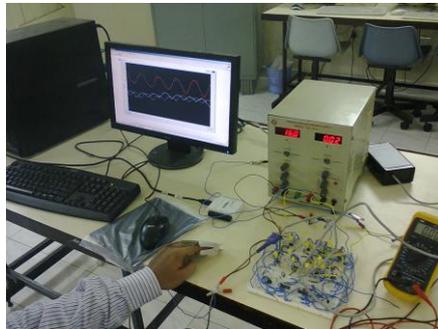
Figure 4. Experimental setup for simultaneous acquisition of PPG and respiratory signals.

To carry out a most meaningful experimentation, data were recorded from subjects from wide age groups in both the genders. Fifty-one subjects participated falling in the age group of 34.6±11.7 (31 male and 20 female) for recording the signals using developed setup. After obtaining the informed consent the signals were recorded from these identified volunteers. Both PPG and respiratory records were collected from each of the volunteers.

4. RESULTS AND DISCUSSION

The recorded PPG and respiratory data were processed and analyzed using signal processing toolbox of MATLAB® R2007b software. In any data-acquisition system, the data obtained will be corrupted by noise (internal-circuit-generated and external noise) and to remove high-frequency noise, the acquired data from the subjects were first filtered using the Savitzky–Golay (SG) smoothing filter, as SG filters are optimal and provide minimum least-square error in fitting a polynomial to noisy data.

The data were then down sampled to 125 Hz, before being used for processing by the actual TQWT method, which decently covers information related to heart rate and respiratory along with artifact components and eliminates all the high frequency noise components. As every frame of 60s duration of the down sampled signal was used for processing by the proposed algorithm, it processed 7500 points (samples) in each frame for PPG signals.
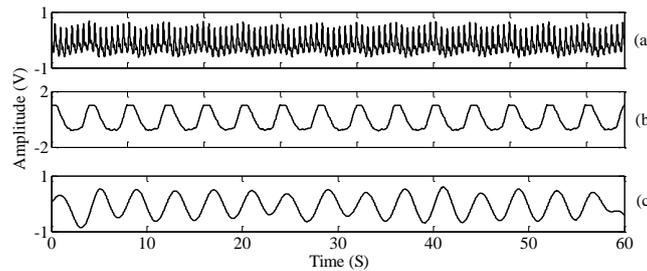
Figure 5. (a) Recorded PPG signal (b) recorded respiratory signal using strain gauge mounted chest belt and (c) the derived respiratory signal using TQWT.
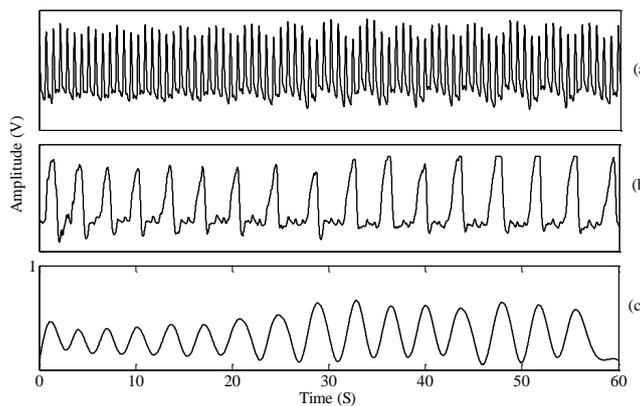
Figure 6. (a) Recorded PPG signal (b) recorded respiratory signal using strain gauge mounted chest belt and (c) the derived respiratory signal using TQWT.

Extraction of respiratory signal

We performed the extraction of the respiratory activity on every 60 sec segment of PPG signal, and then the data were shifted by every 10 s for the entire 5 min of recordings, i.e., each 60 sec dataset had a 50 sec overlap. The respiratory signals were derived using the TQWT recorded PPG signals.
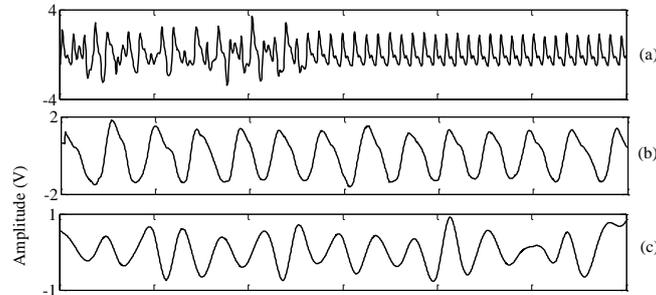
Figure 7. (a) Recorded PPG signal (b) recorded respiratory signal using strain gauge mounted chest belt and (c) the derived respiratory signal using TQWT.
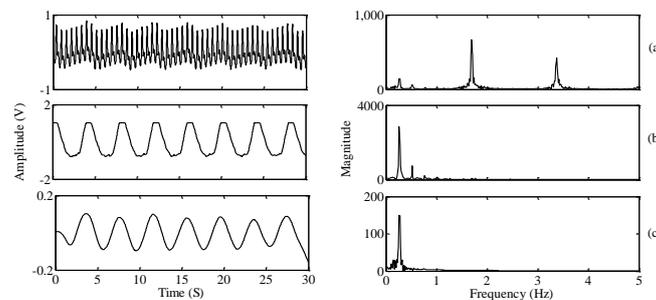
Figure 8. (a) Recorded PPG signal (b) simultaneously recorded respiratory signal using strain gauge mounted chest belt and (c) the derived respiratory signal using TQWT with respective Spectrum.

The PPG signal frequency is 0.007–1.5 Hz, in which the respiratory frequency is from (0.15-0.33) Hz. The respiratory information can be extracted from PPG signal using a simple band pass filter, but the design of narrow band pass filter (NBPF) with classical filter design cannot be possible. Advantage of TQWT stems from the fact that, the realization of practical narrow band pass filter with a specific Q-factor value can be designed, which motivated the authors to use for this application. Here by selecting a Q-factor and redundancy (r) factor such a NBPF can be realizable. To get the desired value of Q-factor, first we apply Fourier transform on the recorded PPG signal and then peak detection algorithm will be applied to identify the heart peak and respiratory peak. For example, if the respiratory peak is identified as 0.25 Hz, and then Q-factor will be 5 for a bandwidth of 0.05 Hz. So, β_{HP} is 1/3 and β_{LP} is 8/9 for redundancy factor of 3.

For a subject (PPG #05) recorded PPG signal, reference respiratory signal and the extracted respiratory signal using TQWT method are shown in Fig. 5(a), (b) and (c) respectively. For more clarity, results for two more subject (PPG #052 & #053) are shown in Fig. 6 & Fig. 7 respectively. It can be clearly seen from these figures that the extracted respiratory signals have strong correlation with their corresponding reference respiratory signal. To provide the spectral validation of the proposed TQWT method, frequency domain version of the recorded PPG, respiratory and extracted respiratory signals are shown in Fig. 8.

Though the visual inspection of the obtained results indicates a close match between derived and original respiratory signals, the performance of the proposed method is evaluated in terms of relative correlation co-efficient (RCC), Magnitude squared coherence (MSC), Accuracy rate (AcR) and normalized root mean square error (NRMSE) which are briefly explained here.

Relative correlation co-efficient (RCC):

It is a time-domain similarity measure defined as

$$RCC = \frac{r_{XY}(0)}{r_{XX}(0)} \tag{6}$$

here, $r_{xy}(0)$ and $r_{xx}(0)$ are the maximum values of cross correlation $r_{xy}(m)$ and autocorrelation $r_{xx}(m)$ respectively, computed on the reference respiratory signal $x(n)$ and derived respiratory signal $y(n)$;

A higher RCC value close to 1 indicates that the extracted respiration is morphologically close to the original respiration in time domain.
Magnitude squared coherence (MSC):

It is a frequency domain similarity measure defined as

$$MSC = \frac{\left|S_{XY}(k)\right|^2}{S_{XX}(k)\,S_{YY}(k)} \tag{7}$$

here, the $S_{xy}(k)$ is the cross power spectral density computed on $x(n)$ and $y(n)$ signals. $S_{XX}(k)$ and $S_{YY}(k)$ is the auto power spectral densities of $x(n)$ and $y(n)$ respectively.

A high value of MSC close to 1 indicates that the frequency content of extracted respiratory signal is almost similar to the frequency content of original respiration signal.

Accuracy Rate (AcR)

It is also a time domain similarity parameter defined on the estimated respiration rate (ERR) obtained from the derived respiration signal and the original respiratory rate (ORR) obtained from the reference respiration signal. The *AcR* in terms of percentage is given by:

$$AcR = \frac{ERR}{ORR} \times 100\% \tag{8}$$

An efficient peak searching algorithm is applied on the extracted and original respiratory signals concerned thereby count for ERR, ORR and subsequently *AcR* are calculated.

Normalized root mean square error (NRMSE)

   It is computed by the following equation

$$NRMSE = \left[\sqrt{\left.\sum_{n=0}^{N}\left[x(n) - y(n)\right]^2 \middle/ \sum_{n=0}^{N}\left[x(n)\right]^2\right.} \right] dB \tag{9}$$

where, $x(n)$ is the original respiratory signal and $y(n)$ is extracted respiratory signal

The lower value of NRMSE is an indication of temporal closeness of the derived respiration to the reference respiration signal.

All the above mentioned performance indices were computed on the extracted surrogate respiratory signal using the proposed TQWT method. Table I indicates the computed MSC, RCC, AcR and NRMSE values for different subjects, which exhibited the ability of the proposed TQWT method in extracting the respiratory signal from PPG.

Table 1. Comparison Of Results Obtained For MSC, RCC, Acr, NRMSE

Data #	PDR with TQWT			
	MSC	RCC	AcR	NRMSE (dB)
05	0.96	0.82	98.75	-14.50
52	0.93	0.71	95.48	-9.45
53	0.94	0.70	100.00	-8.54
55	1.00	0.76	99.32	-10.40
65	0.99	0.79	99.45	-4.63
69	0.99	0.77	97.52	-1.72
141	0.99	0.71	99.54	-10.40
155	0.97	0.74	98.94	-5.63
211	0.99	0.77	98.48	-3.72
216	0.96	0.69	97.26	-2.57
254	0.96	0.80	96.87	-3.51
408	0.96	0.76	99.61	-3.41

5. CONCLUSIONS

In many medical exigency situations such as ambulatory monitoring, during anesthesia, post operative intensive care, monitoring respiratory signal is highly desirable. The fact that the pulse oximeter's photoplethysmographic (PPG) signals contain respiratory information along with heart beat synchronous information. This has motivated many researchers proposing different techniques for the extraction of respiratory signals from PPG. In this paper, we presented a simple yet an efficient method, based on tunable Q-factor wavelet transform (TQWT), which resulted with accurate extraction of respiratory information. The statistical analysis performed on the extracted and original respiratory signals have clearly established the fact that a pulse oximeter can be used to record the respiratory signals along with its routine purposes of montoring arterial blood saturation and the heart rate monitoring.

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AUTHORS

K. Venu Madhav (M'10) was born in Nizamabad, India, in 1975. He received the B.E. degree from Dr. Babasaheb Ambedkar Mararthwada University, Aurangabad, India, in 1997 and the M. Tech. degree from Jawaharlal Nehru Technological University (JNTU), Kakinada, India, in 2008 and Ph. D from JNTUH, Hyderabad. He is currently working as a Professor in the Department of Electronics and Instrumentation Engineering, Kakatiya Institute of Technology and Science, Warangal, India. His research interests include instrumentation, biomedical instrumentation, and digital signal processing.