Non-Contact Dual Pulse Doppler System based Respiratory and Heart Rates Estimation for CHF Patients

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***Abstract*— Long term continuous patient monitoring is required in many health systems for monitoring and analytical diagnosing purposes. Most of monitoring systems had shortcomings related to their functionality or patient comfortably. Non-contact continuous monitoring systems have been developed to address some of these shortcomings. One of such systems is non-contact physiological vital signs assessments for chronic heart failure (CHF) patients. This paper presents a novel automated estimation algorithm for the non-contact physiological vital signs assessments for CHF patients based on a patented novel non-contact biomotion sensor. A database consists of twenty CHF patients with New York Heart Association (NYHA) heart failure Classification Class II & III, whose underwent full Polysomnography (PSG) analysis for the diagnosis of sleep apnea, disordered sleep, or both, were selected for the study. The patients mean age is 68.89 years, with mean body weight of 86.87 kg, mean BMI of 28.83 (obesity) and mean recorded sleep duration of 7.78 hours. The propose algorithm analyze the non-contact biomotion signals and estimate the patients' respiratory and heart rates. The outputs of the algorithm are compared with gold-standard PSG recordings. Across all twenty patients' recordings, the respiratory rate estimation median accuracy achieved 92.4689% with median error of ±1.2398 breaths per minute. The heart rate estimation median accuracy achieved 88.0654% with median error of ±7.9338 beats per minute. Due to the good performance of the propose novel automated estimation algorithm, the patented novel non-contact biomotion sensor can be an excellent tool for long term continuous sleep monitoring for CHF patients in the home environment in an ultra-convenient fashion.**

I. Introduction

Obstructive sleep apnea (OSA) is a common and potentially lethal sleep disorder affecting at least 4% of adult males and 2% of adult females world-wide [1]. Recent statistics published in 2013 reported that the prevalence of OSA had increased to 10 – 17% for males and 3 – 9% for females in the United States of America [2]. OSA is the cessation of airflow due to the collapse of the upper airway during sleep [3] and can occur at any age, from infancy to old age. Statistics has shown that the male to female ratio is about 2:1 and probably affects prepubertal males and females at equal rates [4]. Growing evidences has indicated that OSA is associated with ischemic heart disease, increased prevalence of stroke, coronary artery disease, atrial fibrillation, chronic heart failure (CHF) and cardiac sudden death [5]. Recent cohort study published in 2014 indicated that people with moderate to severe OSA has an increased mortality up to 4 times, nearly 4 times more likely to have a stroke, 3 times more likely to die from cancer and 2.5 times more likely to develop cancer [6]. It is also important to indicate that, according to the Sleep Heart Health Study, OSA & CHF are associated with an increased prevalence of 2.38 times, independent of other known risk factors [7]. These findings have highlighted the significant of OSA and cardiovascular comorbidities.

Sleep medicine researchers to date primarily focus on measurements in controlled artificial environment, such as sleep laboratory, using Polysomnography (PSG) technology to diagnose OSA. Despite the quality and reliability of the PSG system, it is not well suited for long term continuous monitoring [8] and poses limited mobility, causing irritations, distress and discomforts to the patient under monitoring [9]. These limitations have led to stronger demands for non-contact continuous monitoring for sleep.

Even though there are enormous published literatures regarding non-contact assessments of respiratory and heart rates for both healthy and sleep disordered breathing (SDB) subjects, however, the sleep application of non-contact physiological vital signs assessments for CHF patients has been limited. It is also important to emphasize that the majority of current reported achievements for non-contact physiological vital signs estimations are based on 'stationary' and 'direct facing' subject measurements, which is not an ideal scenario for the complexity of sleep environment.

This paper presents a novel automated estimation algorithm based on signals separation, reconstruction, demodulation, and respiratory and heart rates estimation for non-contact physiological vital signs assessments for CHF patients. This paper organized as follows: section II described the non-contact biomotion sensor that tracks a person's movement while sleeping using a radiofrequency motion sensor. Based on these signals, respiratory and heart rates can then be estimated using the propose algorithm as explained in section III. While section IV report the outputs of the algorithm as compared with gold-standard PSG recordings when applied to recordings from a set of twenty CHF patients who presented at a hospital sleep laboratory for evaluation of SDB. Finally, section V concludes the work presented in this paper.

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II. BIOMOTION SENSOR & PATIENTS DATABASE

A. SleepMinder™ Biomotion Sensor

SleepMinder™ (SM), as shown in "Fig. 1", is a ResMed patented novel sensor technology for contactless and convenient measurement of sleep and breathing in the home. SM is a dual pulse Doppler system designed to transmitting two short pulses of radio frequency energy at 5.8 GHz, emits an average power less than 1 mW, and is capable of measuring movements at distance between 0.5 – 3.0 m, nominally. The core architecture of the sensor is that it generates pairs of pulses with the first pulse as the transmit pulse and the second pulse as the mixer pulse. The first pulse reflects off nearby objects to create an echo pulse that is received back in the sensor. By multiplying the echo pulse with the mixer pulse inside the receiver, a continuous output signal proportional to any phase shift of the echo pulse is generated. SM sensor also employed quadrature detection technique to overcome well known limitation in radio frequency sensing called the range-correlation effect, which leads to two estimates of the movements signals, called I & Q channels. In the case of two people lying on the bed, a combination of sophisticated sensor design and intelligent on-board signal processing results in measuring only the motions of the person nearest to the sensor. The output I & Q channels are internally filtered by active analogue low-pass filters at 1.6 Hz, and sampled at 64 Hz with 12 bits resolution and 0 – 3.2 V voltage resolution. The 64 Hz samples are then averaged over 4 samples, producing two 16 Hz channels and saved to the SM flash SD memory card in a proprietary binary format.

Figure 1. ResMed SleepMinder™ non-contact biomotion data logger unit

B. Patients Database

A database of patients was obtained under ResMed's IP agreement. The database consists of twenty CHF patients with New York Heart Association (NYHA) heart failure Classification Class II & III. The patients groups are of 1 female, 18 males and 1 undisclosed, who were sequentially admitted in the Royal Brompton Centre for Sleep, London, UK, for the diagnosis of sleep apnea, disordered sleep, or both. The patients mean age is 68.89 years, with mean body weight of 86.87 kg, mean BMI of 28.83 (obesity) and mean recorded sleep duration of 7.78 hours. The patients had the clinic's ethics approval and written consent obtained, and underwent full PSG analysis with manually scored by sleep experts. SM was installed in the sleep laboratory and its biomotion signals were recorded simultaneously with the PSG signals. SM was placed facing the patient in line with chest at a distance of approximately 0.5 m and an elevation of approximately 0.5 m from the edge of the bed.

III. AUTOMATED ESTIMATION ALGORITHM

This paper introduces a novel automated estimation algorithm pioneering the estimation of respiratory and heart rates for CHF patients in the complexity of sleep environment. The automated estimation algorithm is designed based on the arrangement of three key components:

- Signals Separation & Reconstruction (SSR).
- Signals Demodulation (SD).
- Respiratory & Heart Rates Estimation (RHE).

The automated estimation algorithm is presented in a block diagram as shown in "Fig. 2". The "Detrend" and "Wavelet Packet Decomposition" are sub-components of SSR component. The "Gram-Schmidt Orthogonalization", "Arctangent Demodulation", "Motion Scaling" and "Butterworth Filters" are sub-components of SD component. The two final rates estimation blocks are the sub-components of RHE component.

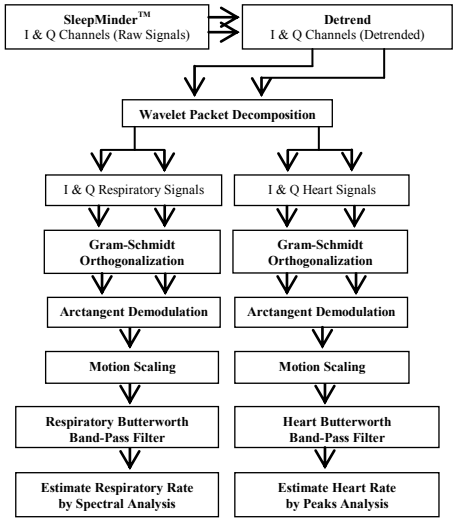

Figure 2. Automated estimation algorithm block diagram

A. Signal Separation & Reconstruction Component

Wavelet analysis is a powerful and popular tool for the analysis of non-stationary signals. Wavelet Packet Decomposition (WPD) has been chosen instead of Discrete Wavelet Transform (DWT) is because both 'approximations' and 'details' coefficients are required to separate the respiratory and heart signals. To determine the choice of the wavelet filter and order, we compare the performance of some known wavelet families, such as, Haar, Daubechies, Symlets and Coiflets. Our performance results indicated that the Symlet wavelet with filter order of 4 gives the most optimum accuracy and a balance of computational time.

Prior decomposing the signals, DC offsets were removed by applying Detrend method, which subtract the mean from the signals. Based on the SM sample rate, both I & Q channels are decomposed to 4^{th} level with both 'approximations' and 'details' coefficients decomposed.

From the decomposed 'approximations' and 'details' coefficients, the frequency band of interest for respiratory signal is 0 – 5 Hz, corresponds to 0 – 30 breaths per minute and heart signal is 0.5 – 2.0 Hz, corresponds to 30 – 120 beats per minute. The decomposed I & Q respiratory signals are then reconstructed at the 4th level using the 'approximations' coefficients. The decomposed I & Q heart signals are then reconstructed from the sum of both 3rd & 4th level using the 'details' coefficients.

B. Signal Demodulation Component

In Doppler radar system, the most important limitation in measuring periodic motions such as respiratory and heart rates are the presence of null-points. The arctangent demodulation method is one of prevailing solution which combines the in-phase and quadrature baseband signals into single channel to eliminate null-points. Prior demodulation, Gram-Schmidt procedure was employed to correct both respiratory and heart signals imbalances. Arctangent demodulation is then performed to extract the phase-modulated signals. The extracted phase-modulated is then multiplied with a motion scaling factor to obtain the respiratory and heart motions. The motion scaling factor is (λ / 4π), where $\lambda = 3 \times 10^8$ ms^{-1} / 5.8×10^6 Hz. A Butterworth 6th order band pass filter (BPF) with frequency bandwidth of 0.2 – 0.5 Hz corresponds to 12 – 30 breaths per minute is applied to the respiratory motions to eliminate clutters, heart motions, movements and noises. A Butterworth 6th order BPF with frequency bandwidth of 0.7 – 1.6 Hz corresponds to 42 – 96 beats per minute is applied to the heart motions to eliminate respiratory motions, movements and noises.

C. Respiratory & Heart Rates Estimation Component

The estimation of respiratory and heart rates employed two analysis methods. The respiratory rate estimation uses spectral analysis, which employs Short Time Fourier Transform (STFT) with a fixed window width of 60 seconds (2 epochs) and a sliding fixed window width of 30 seconds (1 epoch). For each fixed window width, Fast Fourier Transform (FFT) is performed and the spectrum magnitudes are smoothed by applying cubic Savitzky-Golay filter. The smoothed magnitude peaks are then identified and sorted in descending order. The respiratory rate is then calculated from the associated frequency of the first sorted peak, multiplied by 60 seconds to obtain the breaths per minute. The heart rate estimation uses time-domain peaks analysis with the same window and sliding window width as used in spectral analysis. For each fixed window width, local maxima are identified and the heart rate is then calculated from the sum of the number of identified local maxima to obtain the beats per minute.

IV. Performance Measures

In able to compare the outputs of the algorithm with the gold-standard PSG recordings, PSG RIP Thorax sampled at 32Hz and ECG sampled at 256Hz signals were selected. However, since the sample rate of the PSG signals differs from SM sample rate, therefore, RIP Thorax signal is down-sampled to SM sample rate and the SM extracted heart motions is up-sampled to ECG sample rate. The respiratory rate estimation of the down-sampled RIP Thorax is performed via Detrend, WPD, respiratory Butterworth 6th order BPF and spectral analysis. This ensures similar mechanism is applied to both SM and PSG respiratory rate estimations for accurate comparison. The ECG heart rate estimation utilized a reliable real-time QRS detection algorithm by Pan-Tompkins [10] to extract the R-wave peaks. The ECG heart rate is then calculated from the number of identified R-peaks within the fixed window as used by SM peaks analysis to obtain the beats per minute. This ensures reliable and accurate comparison.

Equation (1) is used to find the mean accuracy percentage for single patient when SM estimated rate is less than PSG estimated rate, with 'N' equal the total number of estimated data points:

$$mean\ accuracy\ (\%) = \frac{\sum_{n=1}^{N} 100\left(\frac{SM\ estimated\ rate\ [n]}{PSG\ estimated\ rate\ [n]}\right)}{N} \quad (1)$$

Equation (2) is used to find the mean accuracy percentage for single patient when SM estimated rate is greater than PSG estimated rate:

$$mean\ accuracy\ (\%) = \frac{\sum_{n=1}^{N} 100 - \left(100\left(\frac{SM\ estimated\ rate\ [n]}{PSG\ estimated\ rate\ [n]}\right) - 100\right)}{N} \quad (2)$$

Equation (3) is used to find the mean error for single patient in comparison between the SM estimated rate and PSG estimated rate:

$$mean\ error = \frac{\sum_{n=1}^{N} |PSG\ estimated\ rate\ [n] - SM\ estimated\ rate\ [n]|}{N} \quad (3)$$

V. Results & Discussions

A patient (out of 20) was selected as an example to demonstrate the accuracy of the automated estimation algorithm and is shown in "Fig. 3". As can be seen from "Fig. 3", the SM estimated respiratory & heart rates track along exceptionally well with the PSG RIP Thorax and ECG estimated respiratory & heart rates for the whole duration of the sleep recording of 6.389 hours (367987 samples). The spikes are those periods correspond to significant body movements and the differences in the x-axis are due to the down-sampled & up-sampled data.

The performance measures were obtained for all twenty patients and are shown in "Fig. 4" and "Fig. 5". Across all twenty patients' recordings, the respiratory rate estimation median accuracy achieved 92.4689% with median error of ±1.2398 breaths per minute. The heart rate estimation median accuracy achieved 88.0654% with median error of ±7.9338 beats per minute.

The outliners on the statistical analysis box whisker plot for respiratory rate estimation correspond to patients whose PSG and SM data contains significant body movements, noises and signals dropouts during the sleep recording. The

challenges that affects the accuracy of the heart rate estimation is the condition of 'bradycardia' or 'tachycardia' during sleep and body movements. Predefined signal decomposition, demodulation and static filtering have not been able to adapt in this case. CHF patients in particular, or sleep subjects in general, poses greater challenges in the non-contact signal processing of heart rate estimation.

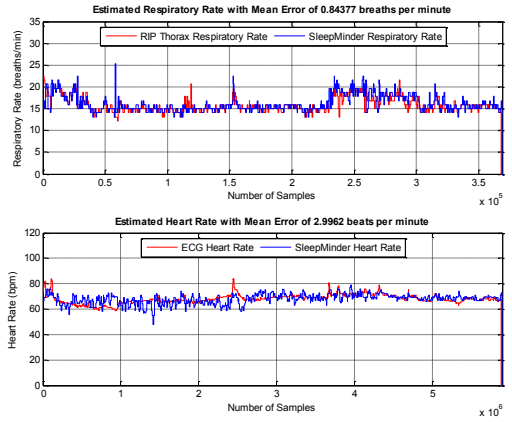

Figure 3. SM & PSG estimated respiratory and heart rate

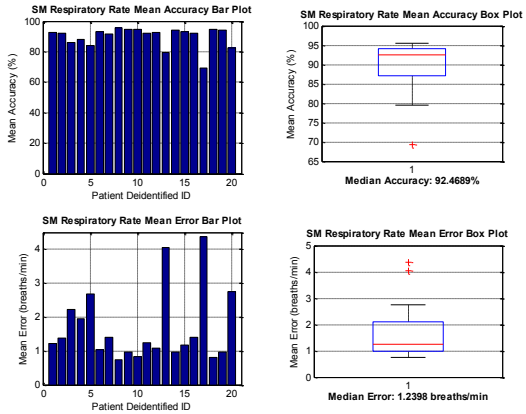

Figure 4. SM estimated respiratory rate mean accuracy and error

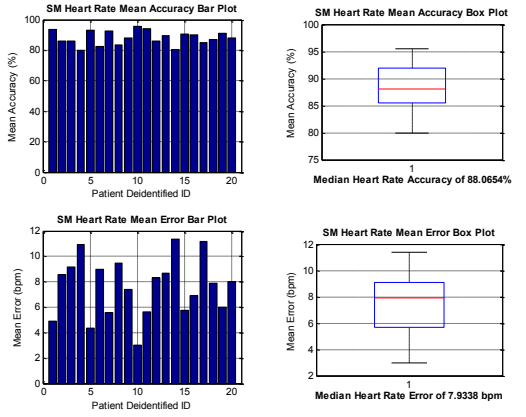

Figure 5. SM estimated heart rate mean accuracy and error

Future directions to address the accuracy challenges in respiratory and heart rates estimations should focus on accurate assessment of the subject's chest displacements, probably using full non-linear phase demodulation and adaptive filtering techniques. The goal is to precisely eliminate unwanted frequencies, separating 'bradycardia' from respiratory and 'tachycardia' from body movements.

VI. Conclusion

The novel automated estimation algorithm has been demonstrated with good accuracy for twenty CHF patients in the complexity of sleep environment. A potential application would be home continuous sleep and circadian rhythm monitoring. Further work will focus on 'bradycardia', 'tachycardia', body movements and undesired harmonics.

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