Contact-free Estimation of Respiration Rates during Sleep

Vishalini Vasu*, Conor Heneghan†, Sakir Sezer *, Thianantha Arumugam*

**The Institute of Electronics, Communications and Information Technology,*
Queen's University Belfast,
Northern Ireland, United Kingdom.
Email :{vvasu01, s.sezer, tarumugam01}@qub.ac.uk

† BiancaMed Limited, NovaUCD, Belfield Innovation Park,
Belfield, Dublin 4,
Ireland
E-mail: conor.heneghan@biancamed.com

Abstract—**A 5.8GHz multi-channel Doppler radar bio-motion sensor for contact-less and convenient measurement of respiration rate in the home was developed and used to measure respiration of a subject. This paper reports on the accuracy of the non-contact sensor respiration rate estimates obtained using signal processing methods compared to a gold standard reference of expert manually scored respiration rates obtained through Polysomnography (PSG) in an accredited sleep lab. Overnight non-contact and PSG recording of 129 patients were carried out. Data from 10 patients were selected for analysis in this paper. Comparison to expert annotation indicates excellent results with only 2.69% error between the non-contact estimates and expert annotation across all subjects.**

Keywords – Biomedical signal processing, respiration rate detection, Doppler radar, non-contact monitoring

I INTRODUCTION

Vital signs are measurements of the body's most basic functions. The four main vital signs routinely used in medicine are pulse rate, respiration rate, body temperature and blood pressure. Respiration rate measurement is vital to clinically evaluate respiratory disorders such as asthma and pneumonia in human beings. Average respiration rate in healthy adults at rest is usually between 12 to 20 breaths per minute (bpm). A change in respiration rate especially in emergency situations is a strong indicator of deteriorating health condition. One way of measuring respiration rate is by counting the number of breaths for one minute by observing how many times the chest rises.

More often in clinical measurements, respiration rate is measured by obtaining changes in chest and/or abdominal volume by the fastening of belts around these areas. This method is known as Respiratory Inductance Plethysmography (RIP). The belt will exhibit a change in tension as the chest or abdomen expands or contracts. This change in tension is measured and converted to respiration rate estimates. However, this method requires accurate placing and tightness of the belt. To obtain quality signals, the belts should be placed at the standard locations: near the nipple line or mid-chest and just above the belly button [1]. The belts also must not be too tight or too loose in order to reflect the patient's true respiration efforts.

There is a lot of interest in less-expensive sleep monitoring alternatives using unobtrusive methods and a self-operated home recording system. These systems could provide be an alternative for clinical diagnosis in some conditions, in particular to act as preliminary screening before further clinical tests are carried out. In view of this, a range of devices and algorithms have been developed in recent years. Alihanka et al [2] and Jansen et al [3] developed a static charge sensitive bed which consists of two sheets of material that act as a motion detector embedded in a mattress. The signal obtained is then digitally filtered and a method of extracting the respiration signal based on piecewise linear approximation was used. Wang et al [4] and Jacobs et al [5] developed a polyvinylidene fluoride (PVDF) piezopolymer film sensor to be used on an ordinary bed. The signal processing algorithm identifies the signals of interest by filtering out irrelevant signals obtained using the sensor. Chee et al developed an air mattress sensor system with a balancing tube and obtained signals by measuring the pressure changes [6]. The signal was then filtered to separate the heart and respiration signals. The first derivative of the filtered signal is used to derive the rate. Spillman et al developed 'smart' beds by integrating fibre optic sensors into bed which reflect

the patient movement and produce a change in the optical signal to monitor patients' movement, respiration and heart rate [7]. They then process the signals by separating the heart and respiration rates and then use the DFT method to extract respiration rate.

All these methods require special beds or mattresses which lead to the argument that the difference in feeling of beds affects the patient sleep. Hence, the recording may not be a true indicator of the patients' daily sleep. The non-contact Doppler radar sensor is very useful to the sleep research community as it allows sleep monitoring in the home environment. Also, the sensor can be used to track a person's movement and respiration patterns while in bed. The goal of this study was to estimate respiration rate from signals acquired through a Doppler radar sensor without the need of contact with subject. The non-contact respiration rate estimates were obtained using algorithm utilising the Lomb method and were compared to gold standard expert annotated respiration rate estimates from signals obtained through Polysomnography (PSG) from sensors in contact with the subject in an accredited sleep laboratory.

II METHODOLOGY

a) Hardware

A 5.8GHz multi-channel Doppler radar bio-motion sensor was developed for non-intrusive and convenient measurement of sleep and respiration in the home. It continuously measures bio-motion due to respiration and body-movement of a subject in bed. Using this device, the limitations arising from basing a diagnosis on a single night's recording, as in the case of PSG, can be overcome. While the PSG requires bulky apparatus and human operation under specific laboratory conditions, the non-contact sensor is an easy-to-use, lightweight and portable device. It is a custom-designed multi-channel 5.8-GHz Doppler radar sensor based on quadrature operation. The channels on the sensor are the baseband in-phase (I) and quadrature (Q) signals referred to as NC-I and NC-Q hereafter in this text. This bio-motion sensor is aimed at evaluating different aspects and problems associated with remote sensing of human vital signs, particularly prospective signal levels, and additional functionality such as restriction of the measurement zone of interest. The sensor operates in a continous wave mode with typical emitted power of 1mW.

The sensor can also be connected to a plug-and-play device like the National Instruments USB-6211 that can be installed directly to a USB drive on a computer to perform real-time data acquisition. Wires representing each acquisition channel can be directly connected to terminals on the NI USB-6211. The NI USB-6211 samples the data at a chosen sampling rate and makes them available digitally to a suitable computer running Matlab or other data-logging software, for example NI LabVIEW SignalExpress. Data that is acquired can then be analyzed and signal processing can be carried out.

b) Database

The database for the study consisted of 10 subjects from 159 subjects who were admitted to the sleep laboratory at St. Vincents Private Hospital, Dublin, between November 2007 and June 2009 because of suspected sleep disorders such as apnoea. All subjects underwent full PSG analysis, manually scored by a sleep expert. The study had hospital ethics approval and written consent from each subject. Patients with sleep disordered breathing (SDB) display apnoeas and hypopnoeas of both a central and obstructive nature. The Apnea-Hypopnea Index (AHI) as shown in Table 1 is used as a quantitative measure of these events during sleep. Data from 10 patients free from sleep disorders (AHI<5) as diagnosed through the overnight PSG study were selected for analysis in this paper. In this measurement, respiration rate estimates from the non-contact sensor were compared against a gold standard reference of expert manually scored respiration rates from the PSG data.

Table 1 AHI Scoring for Sleep Disorders

Normal (AHI<5)
Mild Sleep Disordered Respiration (5≤AHI<15)
Moderate Sleep Disordered Respiration (15≤AHI<30)
Severe Sleep Disordered Respiration (AHI≥30)

Table 2 Patient Demographic Information

AHI	Normal	Mild	Moderate	Severe
Total subjects	35	55	28	39
Gender (M-F)	21-14	44-11	27-1	37-2
Mean Age [yrs]	48.1 ± 4.7	53.1 ± 2.8	55.4 ± 1.7	59.0 ± 13.5
Mean BMI [Kg/m2]	29.2 ± 4.7	29.9 ± 4.9	30.3 ± 5.6	33.4 ± 4.6

c) *Experiment Setup*

The sensor was placed, facing the subject, in line with chest at a distance of approximately 0.2 meters and with an elevation of approximately 0.5 meters from the edge of the bed and facing towards the torso of the subject. The non-contact sensor detects the raw movement of the person's chest which is dominated by respiration. Any movement in the human body will cause disturbance to the non-contact signal which is very weak compared to the signals caused by bigger body movements. The main challenges in the experiment setup were to obtain continuous simultaneous measurement of reference and non-contact signals and preserving the signal integrity. The sensor was non-invasive and none of the subjects reported any discomfort caused

by the sensor (emitted power levels are orders of magnitude below recommended safety limits for non-ionizing radiation at 5.8 GHz). Data analysis was performed using Matlab v7.8.

Figure 1 shows a spectrogram of 100s of simultaneous data acquisition from Subject 1 using the non-contact sensor and also the PSG. The top two axes are the non-contact I and Q channels (*NC-I, NC-Q*) respectively and the third axis is the *flow* signal from the PSG. The lower three axes are the spectrograms from the RIP signals - *ribcage*, *abdomen* and *sum* respectively, of the PSG. In the spectrograms, the respiration information is typically present at around 0.2 Hz or 12bpm. It is present on both the NC-I and NC-Q channels and the signals acquired through PSG. From Figure 1, it can be seen that there is a clear trace of an increase in respiration activity to about 3Hz (18bpm) at 100s. Both the non-contact channels also track this change in respiration activity. It is evident that respiration information is being detected by the non-contact sensor.

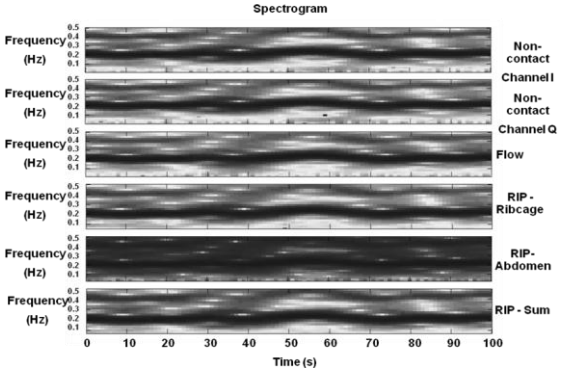

Fig. 1. Spectrogram of data from Subject 1. The top 2 panels are the signal from the sensor; the third is from flow signal and the bottom three are respiratory inductance signals – ribcage, abdomen and sum.

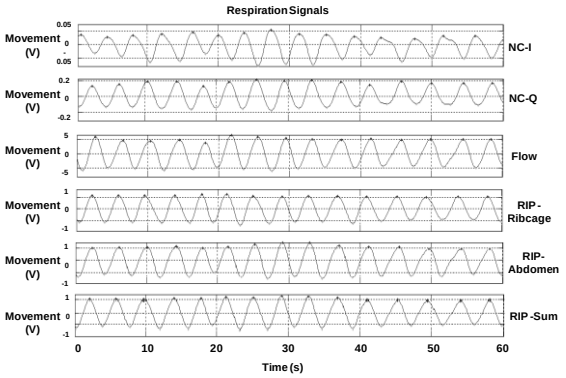

Fig. 2. Simultaneously recorded respiratory movement signals from Subject 1 over a 60-second period. All 6 axes indicate a perfect agreement of 15bpm.

Figure 2 shows a section of the non-contact channels and the PSG signals in the time-domain. The peaks and troughs in 1 minute of data are marked by dots for each of the six axes. The respiration rate for that 60s period can be obtained by calculated the peaks between 500s and 560s. The number of peaks in all the 6 axes is 15 corresponding to a respiration rate of 15bpm in that 60s window. This shows that the non-contact sensor is in agreement with the PSG and has the ability to detect respiration information on a beat per beat basis.

d) Signal processing

The Lomb periodogram can be used for spectral analysis of unevenly sampled data. Commonly used traditional spectral analysis methods such as Fast Fourier Transform (FFT) and Autoregressive (AR) modelling require evenly sampled data series for analysis. Situations may occur where evenly spaced data cannot be obtained. This is a common problem in sensing of physiological signals where the lead or sensor attached to the patient's body comes loose and data becomes missing until the sensor or lead is reconnected. In the case of non-contact sensors, these periods could be of very large movements of the patient's body or a large interference in which time the physiological signal is unable to be recovered.

Interpolating the data could solve the problem of missing data but the performance is known to be poor, especially when there are wide data gaps in the series. The data also needs to be resampled if spectral estimators such as FFT are used. Resampling introduces a low-pass effect in the signal which is not desirable in clinical diagnosis where the power ratio between the low and high frequency components may be relevant. The Lomb spectrum has been used in the study of physiological signals such as heart rate because it could clearly show the very low frequency components of instantaneous heart rate [8]. It is a more accurate method as it weights the data on a point by point basis instead of an entire time interval. Hence, the Lomb method has been found to be more suitable than the FFT or AR methods which can introduce a large dispersion when applied to physiological signals such as heart and respiratory signals. The Lomb method has yet to be tested for spectral analysis on non-contact signals although it has been found to produce more robust PSD estimates in heart rate variability analysis compared to AR and FFT methods in presence of noise [9].

As an initial step, in this study, we investigate the performance of the Lomb method in estimating the respiration component in presence of noise, of a subject, when the subject is stationary or semi-stationary (sleeping with occasional movement). Overnight data is collected during patients' sleep, mostly 6 hours in duration. The respiration is extracted from the combined heart and respiration signal.The two-channel raw signal is composed of the heart and respiratory activity, high-frequency signal noise, and occasional signal dispersions of high amplitude, which are generated by movements of the patient when shifting sleep position. The

technical challenge lies in isolating the respiration signal from other moving objects which cause interference and distortion. For times when the subject is sleeping in a stationary position (no movement periods), respiratory-related chest movement (lifting and lowering of thorax during respiration) is the predominant recorded signal. The peak-to-peak chest motion due to respiration in adults ranges from 0.4 to 1.2cm [10]. These shifts are reflected in the sensor signal and respiratory parameters and movement activity can be calculated.

To determine gold-standard respiration rates, 15-minute sleeping periods with relatively little motion artefact were selected based on visual inspection from each subject. The first stage in the pre-processing of the non-contact signal was to identify and isolate the respiration information from movement and interference from other sources in the sleeping environment. This was done by employing a low-pass filter that filters signals with frequencies of 10Hz or higher to both PSG and non-contact signal to remove high frequency signals in the spectrum. The resting respiration rate is generally between 12 and 20 breaths per minute (0.2 to 0.33 Hz). The non-contact data is further processed whereby the signal is effectively band-passed by applying a high-pass followed by a low-pass filter to pass signals with frequencies between 0.1 and 0.4Hz using FIR filters. This selects the range from 6-24 breaths per minute allowing an easier extraction of the respiration frequency. Then, the data was segmented into 30s windows with 29s overlap.

Any body movement or twitches during recording may greatly distort the non-contact Doppler signal. During such intervals, respiration rate could become hardly detectable. Before identifying the respiration signal, artefacts caused by body movements are removed using a threshold method. When an extremely large value, whose absolute value is 4 times larger than the standard deviation of the previously detected "movement-free" signal, is found in the raw signal, the preceding and succeeding 2.5s raw signals are discarded and not used for the estimation of the respiration rate.

A signal processing algorithm that detects respiration activity based on the Lomb implementation in Press and Teukolsky [11] was applied to the non-contact data. For time-series of N data points $Y_j = Y(tj)$ collected at times t_j where j=1, 2...N, with a mean of Y, the Lomb periodogram was computed from:

$$PN(\omega) = \frac{1}{2\sigma^2}\left\{\frac{\left[\sum_j (Y_j - \bar{Y})\cos\omega(t_j-\tau)\right]^2}{\sum_j \cos^2\omega(t_j-\tau)} + \frac{\left[\sum_j (Y_j - \bar{Y})\sin\omega(t_j-\tau)\right]^2}{\sum_j \sin^2\omega(t_j-\tau)}\right\} \quad (1)$$

Where τ is defined by:

$$\tau = \left(\frac{1}{2\omega}\right)\tan^{-1}\left[\frac{\sum_j \sin 2\omega t_j}{\sum_j \cos 2\omega t_j}\right] \quad (2)$$

This results in a spectrum which is closer to the true underlying spectrum than with the inclusion of the signals with movement artefact. In this case, the Lomb periodogram has been successfully used on evenly sampled data with periods of missing sections. The algorithm then selects the frequency with the lowest alpha and associated frequency consistent with the respiratory component. The performance of the algorithm is compared against gold-standard expert annotation.

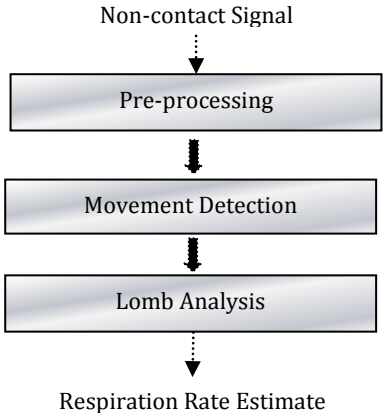

Fig. 3. Main Signal Processing Steps

III PERFORMANCE MEASURE

The performance of the non-contact respiration rate estimates were compared against a gold standard reference of respiration rate by a human expert which is the number of peaks detected by the human expert within a 30 second window. The part of a respiration cycle which is at the edges of the 30 second window is weighted accordingly. The calculation is done using a sliding 30 second window with a 1 second increase. The absolute error is the difference in the number of breaths detected in the non-contact channel with reference to the expert annotated respiration estimates. The channel with a lower error rate is more accurate in respiratory rate detection. A value of 0 indicates perfect agreement.

$$Error\ (beats\ per\ min) = |Expert\ Annotation - Non-contact\ |$$

Or

$$Error\ (percentage) = \left|\left[\frac{(Expert\ Annotation - Non-contact)}{PPG}\right]\right| x100 \quad (3)$$

The SNR of the respiration signal is calculated from the Lomb power spectral density of the non-contact signal. The average rate of the respiration signal from the expert annotation is determined to be the centre of the signal, and the power within ±3bpm of the centre is considered to be the signal power, with all power outside this window considered to be the noise power. The resulting SNR

was plotted against error to indicate whether the SNR does affect the ability to detect respiration rates accurately.

The Bland-Altman analysis [12], comparing the bias magnitude and the standard deviation of the heart rate estimates, are calculated for every 30s epoch of respiratory rate measurement and the resulting Bland-Altman graph was plotted. This plot is more informative than plotting the results of one measurement against the other as the data spread out better. It is also easy to assess bias and variation of the measurements.

IV RESULTS

The average respiration rate extracted from the non-contact signal over all the subjects was highly accurate relative to the expert annotated respiration rate. Across all subjects, the mean respiration rate estimated by the non-contact channels I and Q measured 14.78 and 14.77 breaths per minute respectively while the expert annotated an average of 14.88 breaths per minute from the PSG. Absolute mean error between the non-contact estimates and expert annotation is 0.39 breaths per minute (2.69%) across all subjects for both non-contact channels. Standard deviation of difference between measurements is 0.31 and 0.29 for channel I and Q respectively. Figure 4 shows the expert estimated respiration rates plotted against non-contact respiration rate estimates for 30 respiration rate estimates for a typical subject. The correlation coefficient between the non-contact respiration rate estimates and the expert annotated respiration rate estimates is 0.93 indicating a very high correlation between both estimates.

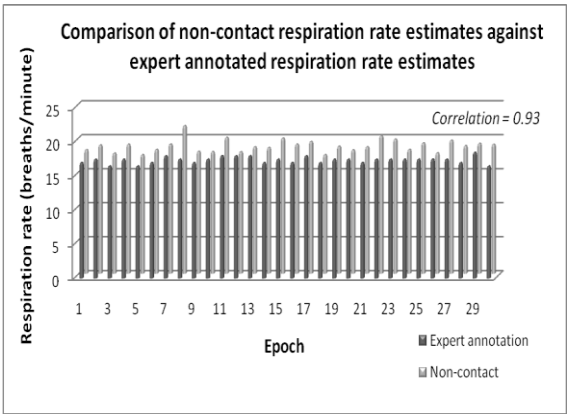

Fig. 4. Histogram of expert estimated respiration rates against non-contact respiration rate estimates

The Bland-Altman graph plots the difference between the non-contact respiratory rates and the expert annotated rates against the mean of the rates. First 200 points are analyzed for each subject and rates calculated every 1 second. Overall, the subjects had, on the average, the Bland-Altman bias magnitude of 0.48 with a standard deviation of 1.01. A typical Bland-Altman plot of 200 non-contact respiration rate estimates against expert annotated respiration rate estimates is shown in Figure 5. Mean was 0.04 and 96% of the estimates were well within the 95% limits of agreement (less than ±1bpm) between the non-contact respiration rates and the expert annotated respiration rate. In 84.5% of the estimates, the error was lower than 0.5bpm (grey band in Figure 5). The Bland-Altman analysis shows that the non-contact respiration rate correlates very well with the expert annotated respiration rate estimates.

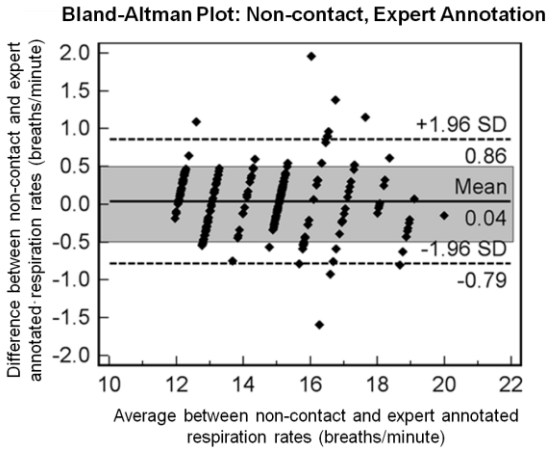

Fig. 5. Bland-Altman plot showing that the 95% limits of agreement between the non-contact and the expert annotated respiration rates are well within ±1bpm

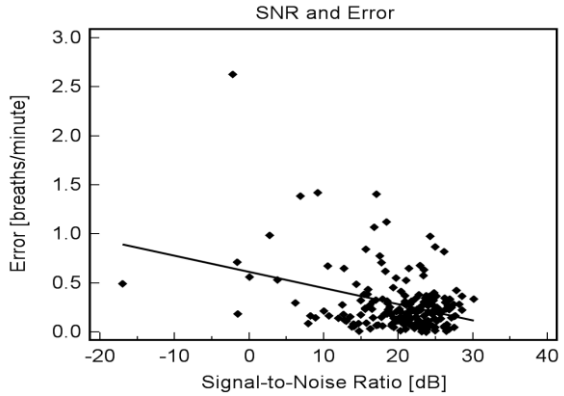

Fig. 6. SNR and error

On average, both the non-contact channels recorded an SNR close to 20dB (NCI - 19.83 ± 4.15, NCQ - 19.43 ± 4.55). Figure 6 shows the plot for SNR against the error between the non-contact sensor and reference measurement. The error is defined as the standard deviation of the difference between the non-contact and reference respiratory rates. The best fit line of the data indicates that standard error increases as the SNR decreases. This indicates that the SNR does affect the ability to detect respiration rates. The accuracy may sometimes be good with an SNR as low as 0dB, but it does not become consistently good until after

10db. Thus, an improvement in SNR will improve the accuracy of respiratory rate detection.

VI CONCLUSION

Extracting respiratory signals in the presence of gross subject motion does limit the capability to obtain accurate rates using a non-contact sensor. However, a non-contact sensor provides a powerful tool for future health monitoring and the signal processing steps described proves successful in estimating respiration rate. A non-contact bio-motion sensor, combined with analysis using the Lomb periodogram can provide reasonable robust and accurate measurements of respiratory rate in sleeping subjects. The use of the non-contact sensor was convenient and unobtrusive. It can be used at home for health monitoring as it is easily automated and can collect data unattended over long periods of time. An increase in SNR could lead to more accurate rates being obtained. The accuracy could be further improved by finding ways to increase the SNR and by using algorithms that can result in the rates being found accurately at lower SNRs. The Doppler radar non-contact sensor is a viable alternative for measuring respiration effort over long period of time which typically requires direct contact with the patient. This technique may be particularly suitable for overnight sleep apnoea monitoring, infant SIDS monitoring and home health care.

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REFERENCES

[1] G. G. Mazeika and R. Swanson, "Respiratory Inductance Plethysmography An Introduction," www.pro-tech.com, 2007, pp. 5-9.

[2] J. Alihanka and K. Vaahtoranta, "A static charge sensitive bed. A new method for recording body movements during sleep," Electroencephalogr. Clin. Neurophysiol., 2009, vol. 46, pp. 731-734.

[3] B. H. Jansen, B. H. Larson and K. Shankar, "Monitoring of the ballistocardiogram with the static charge sensitive bed," Biomedical Engineering, IEEE Transactions on, vol. 38, pp. 748-751, 2002.

[4] F. Wang, M. Tanaka and S. Chonan, "A PVDF piezopolymer sensor for unconstrained cardiorespiratory monitoring during sleep," Int. J. Appl. Electromagn. Mech., vol. 16, pp. 181-188, 2002.

[5] J. L. Jacobs, P. Embree, M. Glei, S. Christensen and P. K. Sullivan, "Characterization of a novel heart and respiratory rate sensor," 26th Annual International Conference of the IEEE EMBS, pp. 2223-2226, 2005.

[6] Y. Chee, J. Han, J. Youn and K. Park, "Air mattress sensor system with balancing tube for unconstrained measurement of respiration and heart beat movements," Physiol. Meas., vol. 26, pp. 413, 2005.

[7] W. B. Spillman Jr, M. Mayer, J. Bennett, J. Gong, K. E. Meissner, B. Davis, R. O. Claus, A. A. Muelenaer Jr and X. Xu, "A 'smart' bed for non-intrusive monitoring of patient physiological factors," Measurement Science and Technology, vol. 15, pp. 1614-1620, 2004.

[8] P. Laguna, G. B. Moody and R. G. Mark, "Power spectral density of unevenly sampled data by least-square analysis: performance and application to heart rate signals," IEEE Transactions on Biomedical Engineering, vol. 45, pp. 698-715, 1998.

[9] G. B. Moody, "Spectral analysis of heart rate without resampling," Proceedings IEEE Computers in Cardiology, pp.715-718, 1993.

[10] T. Kondo, T. Uhlig, P. Pemberton and P.D. Sly, "Laser monitoring of chest wall displacement," Eur. Respiratory J., vol. 10, pp. 1865-1869, 1997.

[11] W. H. Press, S. A. Teukolsky, W. T. Vetterling and B. P. Flannery, "Spectral analysis of unevenly sampled data," Numerical Recipes in C, 1992.

[12] J. M. Bland and D. G. Altman, "Statistical methods for assessing agreement between two methods of clinical measurement," Lancet, vol. 1, no. 8476, pp. 307–310, 1986