Volume 4, Issue 1, January 2014 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

PPG Signal for Extraction of Respiratory Activity and HR Monitoring of CHF Patients

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Abstract- The fact that the Photoplethysmograph (PPG) signal caries respiratory information in addition to arterial blood oxygen saturation attracted the researchers to extract the respiratory information from it. In this current work, we present an efficient algorithm, based on the multi scale principal component analysis (MSPCA) technique to extract the respiratory activity from the PPG signals. MSPCA is a powerful combination of wavelets and principal component analysis (PCA). In MSPCA technique, PCA is used in computing coefficients of wavelet at each scale, and finally combining all the results at relevant scales. With this aim displaying of heart rate and the extraction of respiratory activity is done. MSPCA performed exceptionally well for extraction of respiratory activity from PPG.

Index terms – Heart rate, MSPCA, PCA, Photoplethysmogram (PPG), Respiratory signal, Wavelets.

I. INTRODUCTION

Respiration monitoring is significant in clinical diagnostics, therapeutics, prognosis, during surgical procedures, post-operative care units, in addition to, monitoring sleep disorders, drug administration and cardiopulmonary disorders. Recording respiratory signal is generally carried out by special instruments and techniques like spirometer, pneumo tachometry, capnography, nasal thermistors and whole body plethysmography. This specialized equipment can't be used in all situations and of patient conditions, as the equipment causes either inconvenience or interferes with normal breathing. Therefore methods of extracting respiratory information from more commonly used physiological signals such as electrocardiogram (ECG) and photoplethysmogram (PPG) are always demanded by the physicians, avoiding additional equipment for recording of respiratory activity. Hertzman developed a non-invasive, non-occlusive electro optic method of recording heart related information from variations of the blood volume at a particular test site on the body close to the skin and is called as PPG. A photoplethysmogram is obtained by illuminating a part of the body extremities such as index finger or ear lobe with either infrared or red light and acquiring either the reflected or transmitted light [1]. The PPG signal is composite in nature and has five different frequency components in the interval 0.007–1.5 Hz [2]. Sources of these frequency components may be relating to respiration, blood pressure control, thermoregulation, autonomous nervous system (ANS) and heart synchronous pulse waveform. Out of the five components, only two components dominate the signal, one is due to the pulsatile component corresponding to the blood flow in the vessels, i.e. the arterial pulse, caused by the heartbeat, and gives an alternating signal (AC component) and the other is, large quasi-DC component that relates to the tissues, bones and to the average blood volume which gives a steady signal. The DC component varies very slowly due to Respiration.

The fundamental frequency of pulsatile AC component is usually around 1 Hz, and varies according to the heart rate of subject under test. The pulsatile AC component is superimposed on to a large value of quasi-DC component. Therefore, the PPG signal not only consists of rhythmic heartbeat information but also a periodic respiratory signal with a frequency band of 0.2-0.33 Hz, due to respiratory induced intensity variation (RIIV) in PPG signal. Hence, the heart rate (or pulse rate) and respiratory rate are two important vital signals, they are of great importance in monitoring health of critically ill adults and infants [3]-[4]. Electrocardiogram (ECG) is used in general by the physicians for clinical monitoring as it represents the electrical manifestation of contractile activity of the heart [5]. It is also evident from the literature that the ECG carries respiratory information and hence much work has been done on ECG derived respiratory activity (EDR) [6]-[7]. In past, researchers were attempting to extract the respiratory information embedded in PPG signals in the form of RIIV signal, which includes a simple band pass filter [8], but the band pass filter must be adaptive in nature to allow the band of all possible frequencies corresponding to the respiratory rates. An adaptive band-pass finite impulse response (FIR) filter, designed in frequency sampling method with suitable pass band specifications drawn automatically from the spectrum of the signal itself has efficiently separated heart and respiratory related signals [9]. A bivariate AR modelling algorithm demonstrated a high coherence between respiration and PPG signals [10]. Other significant works done in this direction include a time frequency spectral estimation [11], time varying AR model by *Ki H. Chon et al* [12], an automated wavelet transform method by *P Addison et al* [13] and an order reduced AR method by the authors [14]. In all of the mentioned methods, there is a definite requirement of a prior knowledge of respiratory rate range. Therefore to improve upon the limitations of currently available methods of extracting the respiratory information from the PPG signals, a method based on multi scale principal component analysis (MSPCA) is developed, which is able

to extract the respiratory signal accurately and continuously from non-invasive recordings of artifact corrupted PPG signals. The proposed MSPCA method is a robust yet simple method for acquiring the PPG derived respiratory (PDR) signal. Rest of the paper is organised by acquisition circuit for PPG, displaying the heart rate, and extraction of respiratory information from the PPG signal.

II PPG ACQUISITION SYSTEM

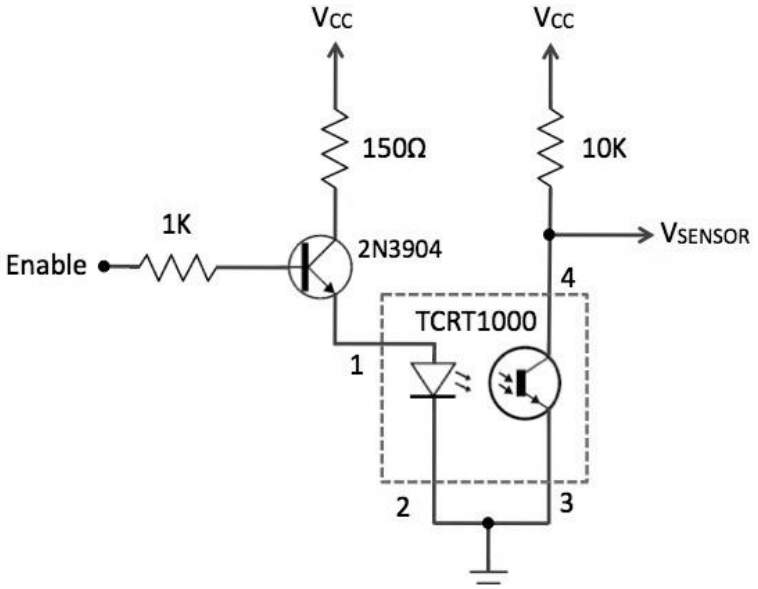

Fig 1: PPG sensor circuit

The sensor used in this project is TCRT1000, which is a reflective optical sensor with both the infrared light emitter and phototransistor placed side by side and are enclosed inside a leaded package so that there is minimum effect of surrounding visible light. The circuit diagram below shows the external biasing circuit for the TCRT1000 sensor. Pulling the Enable pin high will turn the IR emitter LED on and activate the sensor. A fingertip placed over the sensor will act as a reflector of the incident light. The amount of light reflected back from the fingertip is monitored by the phototransistor.

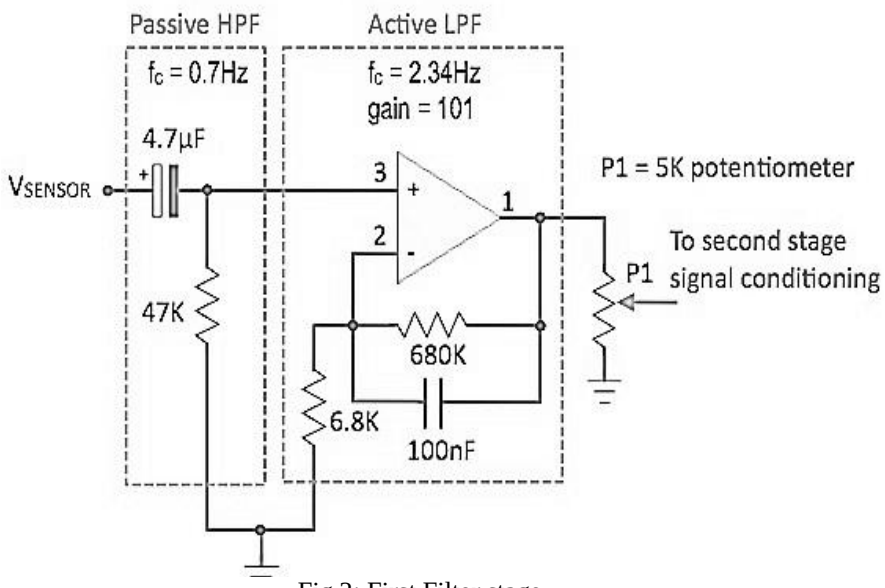

Fig 2: First Filter stage

The output (VSENSOR) from the sensor is a periodic physiological waveform attributed to small variations in the reflected IR light which is caused by the pulsatile tissue blood volume inside the finger. The waveform is, therefore, synchronous with the heartbeat. The following circuit diagram describes the first stage of the signal conditioning which will suppress the large DC component and boost the weak pulsatile AC component, which carries the required information. In the circuit shown in fig 2, the sensor output is first passed through a RC high-pass filter (HPF) to get rid of the DC component. The cut-off frequency of the HPF is set to 0.7 Hz. Next stage is an active low-pass filter (LPF) that is made of an Op-Amp circuit. The gain and the cut-off frequency of the LPF are set to 101 and 2.34 Hz, respectively. Thus the combination of the HPF and LPF helps to remove unwanted DC signal and high

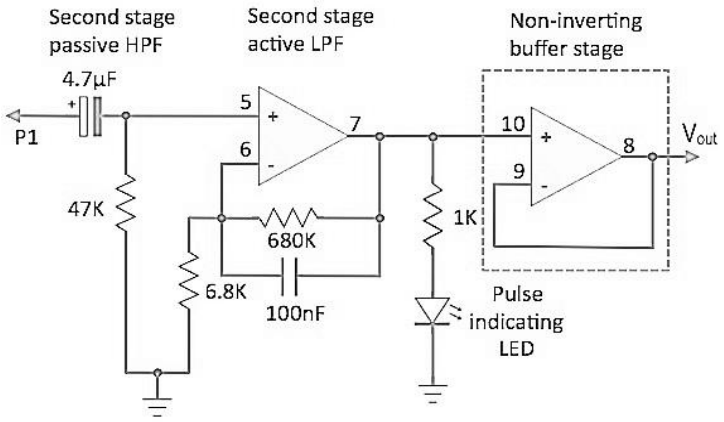

Fig 3: 2nd stage filtering

frequency noise including 60 Hz (50 Hz in some countries) mains interference, while amplifying the low amplitude pulse signal (AC component) 101 times.

The output from the first signal conditioning stage goes to a similar HPF/LPF combination for further filtering and amplification (shown in fig 3). So, the total voltage gain achieved from the two cascaded stages is 101*101 = 10201. The two stages of filtering and amplification converts the input PPG signals to near TTL pulses and they are synchronous with the heartbeat. The frequency (f) of these pulses is related to the heart rate (BPM) as,

Beats per minute (BPM) = *60*f*

A 5K potentiometer is placed at the output of the first signal conditioning stage in case the total gain of the two stages is required to be less than 10201. An LED connected to the output of the second stage of signal conditioning will blink when a heartbeat is detected. The final stage of the instrumentation constitutes a simple non-inverting buffer to lower the output impedance. This is helpful if an ADC channel of a microcontroller is used to read the amplified PPG signal.

For the counting purpose both the timers of 8051 (Timer0 and Timer1) are used. Timer 1 is configured as an 8 bit auto reload counter for registering the number of incoming zero going pulses and Timer0 is configured as a 16 bit timer which generate the necessary 1 second time span for the Timer1 to count. For counting the number of beats Timer0 and Timer1 are used. Timer1 is set as an 8 bit auto reload counter for counting the number of pulses (indicating the heart beat) and Timer0 is set as a 16 bit timer which generates a 65536uS delay. When looped 230 times it will produce a 15 second time span (230 x 65536uS =15S) for the Timer 1 to count. The number of counts obtained in 15 seconds is multiplied by 4 to obtain the heart rate in beats per minute. The Timer 0 which generates the 1 second time span is configured in Mode 1 (16 bit timer). So the maximum it can count is 2^16 and it is 65536. In 8051 the crystal frequency is divided by 12 using an internal frequency divider network before applying it as a clock for the timer. That means the timer will increment by one for every 1/12th of the crystal frequency. For an 8051 based system clocked by a 12MHz crystal, the time taken for one timer increment will be 1µS (i.e.; 1/12MHz). So the maximum time delay that can be obtained using one session of the timer will be 65536µS. Go through this article Delay using 8051 timer for a better grasp. As shown in Fig 4.

Pulse oximetry, a non-invasive technique developed by Hertzman [3], uses photoplethysmographic (PPG) signals, obtained by opto-electronic recording of the volumetric changes in the arterial blood at a specific point of interest in the body, usually the body extremities like index finger or ear lobe.

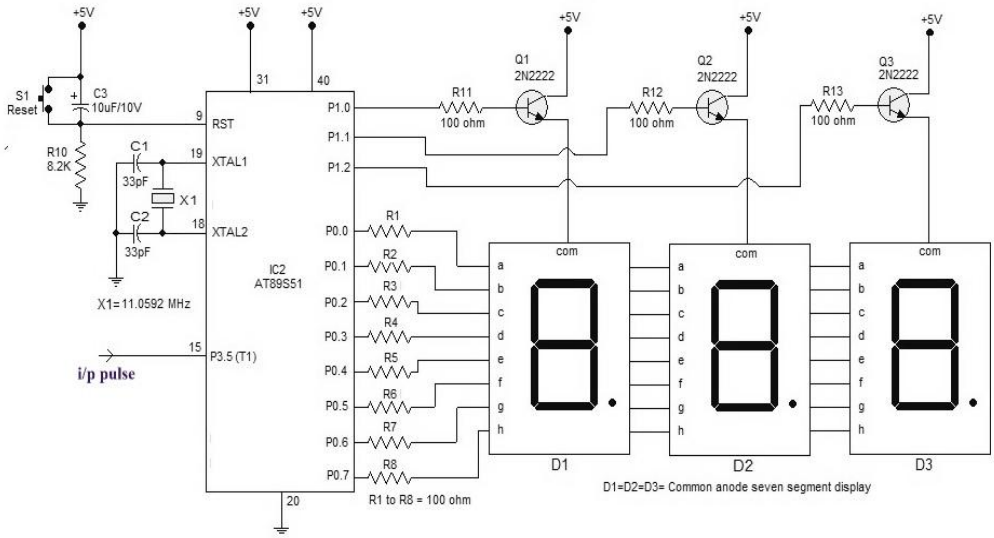

Fig 4: Heart rate monitor using 8051 microcontroller

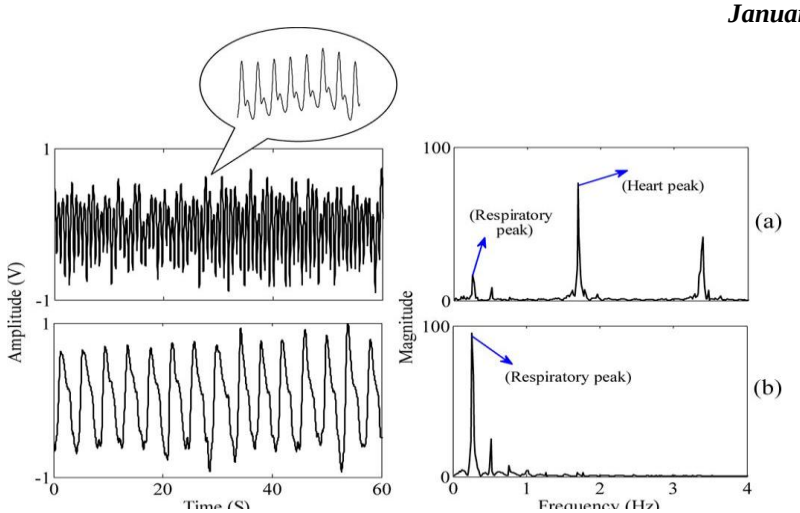

Fig. 5. (a) PPG signal (b) simultaneously recorded respiratory signal for 60 s duration with their corresponding spectra in adjacent column. Respiratory and heart rate peaks are clearly seen in the PPG spectrum along with their harmonics

Respiratory-Induced Modulation of PPG Signals

In fact, two PPG signals are recorded in pulse oximeter at different wavelengths viz., red (660nm) and infrared (940nm) for estimation of the accurate oxygen saturation level in the arterial blood. The recorded PPG signals inherently contain respiratory information as the blood flow to the various body extremities get affected by the movement of thoracic cavity while breathing. Thus, the PPG signals modulated by the respiratory activity can be used for deriving the respiratory signals and become an alternative or indirect method for recording respiratory information. PPG signal is composite in nature and has five different frequency components in the interval 0.007–1.5Hz [4] related to thermoregulation, barorefluxus, autonomous nervous system, respiration, and heart synchronous pulse. The pulsatile component of the PPG waveform is often called as AC component and usually has its fundamental frequency, typically around 1 Hz, depending on heart rate. This ac component is superimposed on to a large Quasi-dc component that relates to the tissues, bones, and to the average blood volume. This dc component varies slowly due to Respiration. As the ac component of the PPG signal is synchronous with the heart beat and thus can be identified as a source of heart rate information. In addition to heart synchronous variations, the PPG signal contains respiratory-induced intensity variations (RIIV) [5]. Along with the RIIV, frequency and amplitude variations are contained in the PPG signal; thus, the relationships between these variations and respiration can be well utilized for monitoring respiration based on PPG [6]. This modulation arises from respiratory induced variations in venous return to the heart, caused by alterations of thoracic pressure. A 60-s data record of PPG obtained from a healthy volunteer, shown in Fig.5, shows two peaks; one at 0.25 Hz (respiratory component) and the other at 1.6 Hz (Heart beat). Simultaneously recorded respiratory signal is also shown is the figure (using strain-gauge mounted chest belt sensor) along with its spectrum confirming the respiratory induced modulation of PPG signal.

Extraction of Respiratory Activity from PPG Signals

Extraction of respiratory information from PPG signal was actually encouraged by the work of many researchers who contributed to electrocardiogram (ECG)-derived respiratory activity. Einthoven *et al.* [7] first studied the effect of movement of thoracic cage while breathing, on ECG signals. Many others proposed algorithms for estimation of respiratory rate as well as for extraction of true breathing pattern [8]. However, the problems associated with extraction of respiratory rate from ECG in clinical settings, in cases of sleep disorder investigations, stress test analysis, etc., where long recordings of respiratory signals are desired, wearing the ECG electrodes for quite longer duration lead to patient discomfort. With these challenges, researchers started attempting the problem of extracting respiratory activity from other vital yet easily obtainable physiological signal having influence of respiratory activity, such as the PPG signals of pulse oximeter, leading to PPG-derived respiratory (PDR) signals.

Nikajima *et al.* [9], first attempted for PDR using a simple band pass filter, but the order of the filter needed was too high to be realized. Other problem with the method was choosing the correct band of frequencies for the filter which would be difficult in many situations such as stress test analysis, drug administration, and chronic pulmonary diseases. A fully automated algorithm based on continuous wavelet transform (WT) by Leonard *et al.* [10], mainly suffers from the problem of respiratory frequency band overshadowed by the unavoidable motion artifacts (MA) leading to incorrect detection of respiration information. Other significant contributions to the field of extraction of respiratory activity from PPG signals include [11]–[13]. A bivariate AR model was proposed by [14], which demonstrated a high coherence between respiration signal and PPG. Recently, Ki H. Chon *et al.* proposed and compared different techniques based on time frequency spectral estimation, for extraction of respiratory rate from PPG signals [15], [16]. The authors proposed a method based on an order reduced modified covariance auto regressive (OR-MCAR) model [17], with promising results, but the method works with an assumption that the breathing rate is known a priori. J. Lee *et al.* proposed AR modelled particle filtering methods for extraction of respiratory rates even if the breathings rates are as high as 90 breaths per minute [18], [19].

Addressing the issues, the authors presented methods based on principal component analysis (PCA) [20] and based on empirical mode decomposition [21], which resulted in surrogate respiratory signals having a higher degree of correlation with the originally recorded respiratory signal by classical methods. Having inspired by, and in continuation to their past work, to refine the results, the authors have proposed a novel technique based on multi scale PCA (MSPCA) [22]1, which combines the advantage of wavelets in time-frequency spectral characterization of the signal by means of signal decomposition, with the PCA. In this paper, we present a robust algorithm, called modified MSPCA (MMSPCA), for extraction of respiratory activity embedded in the PPG signals, which is an extension to our prior work [22]. It has been observed by the authors that the algorithm is not properly extracting respiration in the events of MA. The PPG signals are more commonly corrupted by MA due to voluntary or involuntary movements of the patients which will not only make it difficult in estimation of arterial oxygen saturation but also extraction of respiratory signals. Though, there are contributions in MA reduction for accurate estimation of SpO2 [23], [24], no work has been reported on extraction of respiratory information from MA corrupted PPG signals. At present, different algorithms exists which claim to extract respiratory signal from PPG, but they fail in situations of PPG corrupted with MAs. For instance [25], where motion corrupted segments in the PPG signals were neglected in the extraction of respiratory information. This problem of extracting respiratory signals from PPGs in the presence of MA is addressed for the first time in this paper. The problem gets aggravated when PPGs are severely afflicted with MAs in situations such as the MA frequency band (usually below 0.2 Hz) overlapping on to the band of respiratory frequencies (0.2-0.4 Hz). In the presented algorithm, the kurtosis and energy contribution levels (ECLs) of approximate and detail coefficients are calculated for each wavelet sub-band matrix, generating a modified wavelet sub-band matrix. This makes the presented algorithm based on MMSPCA more robust in the sense that it is made motion resistant by suitably modifying the MSPCA preserving the morphological features of the extracted respiratory signal to a large extent.

III MSPCA

MSPCA is a powerful combination of PCA with wavelets for processing of multivariate statistical data [26]. The WT is an alternate to short-time Fourier transform (STFT) or Gabor transform. STFT uses a single analysis window, whereas the WT uses variable adaptive size window (long window at low frequencies and short window at high frequencies). The WT analysis is similar to time-frequency analysis based on Wigner- Ville distribution. As the biomedical signals are quasi periodic in nature and for processing such signals, wavelet analysis has been proven to be a powerful tool. Discrete WT (DWT) decomposes the given signal into multilevel hierarchic frequency bands similar to filter banks. In DWT, a low-pass filter (LPF) and a high-pass filter (HPF) decompose the signal in to different scales. Coefficients of the LPF are referred to as 'approximations' defining identity and that of the HPF are referred to as 'details,' defining imparts of the signal. The approximated signal may be passed down to next stage for further decomposition by breaking the signal content into many levels of lower and lowest resolution components, resulting with a multi-level decomposition. Therefore, the decomposition process is iterative giving rise to wavelet decomposition tree. A block diagram of three level wavelet decomposition tree is shown in Fig.6, where the output approximate coefficients depicted with A*j* and detailed coefficients are referred as D*j*, giving a complete set of wavelet sub-band at that level. All detailed coefficients along with approximation coefficients of the last level are used to reconstruct original signal using complementary filters, considering 'M' as the length of the coefficients. An *L* level decomposition results in *Lth* approximation subband coefficients *cAL*, and *jth* detailed sub-band coefficients *cDj* , where *j* = 1, 2, . . . , *L. N* number of multivariate signals are collected in a matrix to form a wavelet sub-band matrix. In general, PCA is intended for interpretation of large data sets which can be easily decomposed into smaller blocks or matrices. PCA is used for analyzing linearly mixed data patterns in long data rerecords collected in to a 2-D matrix from stationary process. The PCA analysis is suitable for many signal processing problems encountered in the field of biomedical instrumentation, including PPG

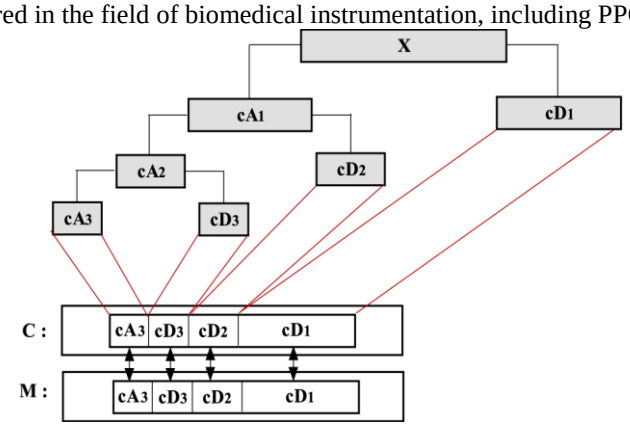

Fig. 6: Wavelet Decomposition Tree.

Signals [27] such as noise elimination, data dimensional reduction, and data compression. In PCA, the principal components (PCs) are either computed using singular value decomposition or by using the covariance matrix. A data set is formed by considering the multivariate data

$X(t) = [x1(t), x2(t), x3(t), \ldots\ldots xm(t)]$ (1)

Where $X(t)$ is the input data with time-ordered collection of the feature at all events into a single matrix to which PCA can be applied. Covariance matrix is computed by removing mean trend from each of the *xi*. Then, the covariance is defined as

$$\Sigma = 1/n[X X^T] \quad (2)$$

Where Σ is an *mxm* square symmetric matrix, for which eigen values (*aj*) and corresponding eigenvectors (λj) are calculated. Eigenvectors are arranged in the descending order of their corresponding eigenvalue. This setting gives us the components in order of significance. The components with less eigen values can be ignored, which forms the basis for signal compression. PCs are ordered depending on their eigenvectors of covariance matrix. The PCs were obtained using

$$z_j = a_j x \quad j = 1, 2, \ldots, n. \quad (3)$$

The PCs are linear transformation of the cycles with transformation coefficients given by the eigenvectors αj. It is the eigenvector which provides the base for PCA in extraction of respiratory signal from PPG signal. PCA provides as many PCs as there are analysed cycles. However, when correlation with that of respiratory component is to be considered, most of the similarity is expressed by the first few PCs only.

The following steps show the implementation details of MSPCA.

Step 1: For each column in data matrix of PPG, perform wavelet decomposition.
Step 2: For each scale, compute covariance matrix of wavelet coefficients.
Step 3: Compute PCA loadings and scores of wavelet coefficients.
Step 4: Select appropriate number of loadings.
Step 5: Select wavelet coefficients larger than appropriate threshold.
Step 6: For all scales together, compute PCA by including scales with significant events.
Step 7: Reconstruct approximate data matrix from the selected and thresholded scores at each scale.

MSPCA has successfully extracted the respiratory signals from PPG [22] and its performance slightly deteriorated in the presence of MAs. The reason for the deterioration of the performance of the MSPCA, in the presence of MAs, is due to noneffective functioning of the thresholding process employed. The thresholding on the wavelet sub-band matrices will eliminate some components to unknown extent leaving a complex signal for further processing, which includes PCA. Hence, reconstructed signal after MSPCA looked different from the original resp. Here, to improve the performance, MSPCA is suitably modified by replacing the simple thresholding of MSPCA with modified sub-band matrices based on kurtosis and ECL. This precisely makes the HR component to get eliminated, thus leaving only resp and MA for further processing.

IV EXPERIMENTAL RESULTS

To verify the practicality of proposed technique for extracting repirogram signal from PPGs the MIMIC database of PhysioNet [16] archive was utilised. PhysioNet provides, large collections of data pertaining to various physiologic signals recorded from different subjects, and it also provides users to access related open-source software. The MIMIC database of PhysioBank archives contain multiple recordings, each of them include ECG, BP, PPG, Respiratory signals which were recorded simultaneously with a sampling rate of 125Hz. The lengths of these records vary, but averaging about each of 40 hours duration. Four records from this database, having continuous recordings of PPG and Respiration without any breaks for about 1 minute duration each, were identified for use in assessing the performance of the algorithm for extraction of breathing information. The proposed method is applied on data records drawn from the MIMIC database and the respiratory signals were extracted and shown as Fig 7. For comparison, the originally recorded respiratory (ORR) signal is plotted along with the extracted ones. Visual inspection clearly shows a strong correlation between the PDR and the ORR and same can be verified with their spectra shown in Fig. 8. Though the visual inspection of the derived respiratory signals indicates a close match with that of reference respiratory signals, a degree of similarity in time domain is quantified in terms of correlation co-efficient *(r)* defined as

$$r=COV(x, y)/\sigma_x \sigma_y \quad (4)$$

Where COV means covariance; $x\ \sigma$ and $y\ \sigma$ are the standard deviations. In addition, a frequency domain measure of similarity, the magnitude squared coherence *(MSC)*, was also estimated for each recording as defined in (5).

$$MSC=|P_{xy}(f)|^2/(P_x(f)\,Py(f)) \quad (5)$$

Where *PXY (f)* is cross power spectral density of original and surrogate respiratory signals, *PX (f), PY (f)* are auto PSDs of original and surrogate respiratory signals respectively.

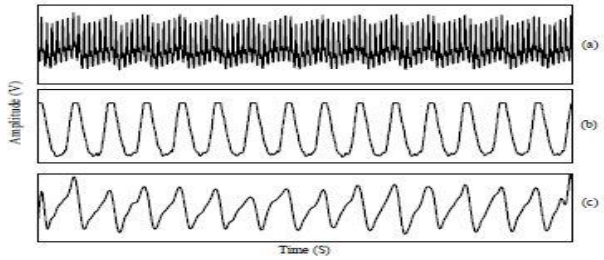

Fig 7: MIMIC database record #041m: (a) PPG, (b) original respiratory signal and (c) extracted respiratory signal using MSPCA method

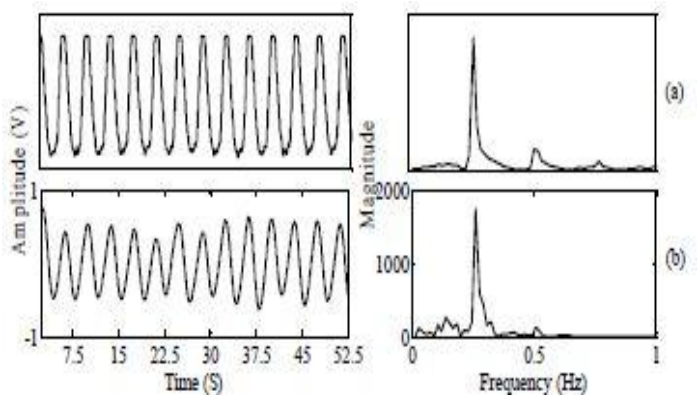

Fig 8: The spectra: (a) Original respiratory signal and its spectrum, (b) Respiratory signal extracted from PPG and its spectrum

V CONCLUSION

Extracting respiratory activity from photoplethys -mographic (PPG) signals has been a challenging problem for the researchers, as it avoids use of additional sensor for recording the respiratory signal in RICUs. A method based on Multi Scale Principal Component Analysis (MSPCA) to extract the respiratory information was addressed in this paper. The ability of PCA combined with wavelet analysis resulted in a highly correlated respiratory signal extraction. Statistical analysis revealed accuracy rates of above 98%, making the MSPCA method promising one for extraction of surrogate respiratory activity from physiological signals having respiratory influence.

REFERENCES

[1] J. G. Webster, *Medical Instrumentation: Application and Design*, 4th Ed. New York: Wiley, 2010.
[2] J. B. West, *Respiratory Physiology: The essentials*. Philadelphia, PA: Lippincott Williams & Wilkins, 2008.
[3] A. B. Hertzman, "The blood supply of various skin areas as estimated by photoelectric plethysmograph," *Amer. J. Physiol.*, vol. 124, no. 2, pp. 328– 340, Oct. 1938.
[4] J. G. Webster, *Design of Pulse Oximeters*. New York: Taylor & Francis, 1997.
[5] A. Johansson, L. Nilsson, S. Kalman, and P. Å. Öberg, "Respiratory monitoring using photoplethysmography," in *Proc. 20th Annu. Conf. IEEE EMBS*, 1998, vol. 20, no. 6, p. 3226.
[6] J. Li, J. Jin, X. Chen, W. Sun, and P. Guo, "Comparison of respiratoryinduced variations in photoplethysmographic signals," *Physiol. Meas.*, vol. 31, no. 3, pp. 415–425, Mar. 2010.
[7] W. Einthoven, G. Fahr, and A. Waart, "On the direction and manifest size of the variations of potential in the human heart and on the influence of the position of the heart on the form of the electrocardiogram," *Amer. Heart J.*, vol. 40, no. 2, pp. 163–211, Aug. 1950.
[8] R. Bailon, L. Sornmo, and P. Laguna, "A robust method for ECG-based estimation of the respiratory frequency during stress testing," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 7, pp. 1273–1285, Jul. 2006.
[9] K. Nakajima, T. Tamura, T. Ohta, and H. Miike, "Monitoring of heart and respiratory rates by photoplethysmography using a digital filtering technique," *Med. Eng. Phys.*, vol. 18, no. 5, pp. 365–372, Jul. 1996.
[10] P. A. Leonard, J. G. Douglas, N. R. Grubb, D. Clifton, P. S. Addison, and J. N. Watson, "A fully automated algorithm for the determination of respiratory rate from the photoplethysmogram," *J. Clin. Monit. Comput.*, vol. 20, no. 1, pp. 33–36, Feb. 2006.
[11] L. Nilsson, A. Johansson, and S. Kalman, "Monitoring of respiratory rate in postoperative care using a new photoplethysmographic technique," *J. Clin. Monit.*, vol. 16, no. 4, pp. 309–315, 2000.
[12] J. Lee, J. P. Florian, and K. H. Chon, "Respiratory rate extraction from pulse oximeter and electrocardiographic recordings," *Physiol. Meas.*, vol. 32, no. 11, pp. 1763–1773, Nov. 2011.
[13] J. Y. A. Foo and S. J. Wilson, "Estimation of breathing interval from the photoplethysmographic signals in children," *Physiol. Meas.*, vol. 26, no. 6, pp. 1049–1058, Dec. 2005.
[14] Y. D. Lin, W. T. Liu, C. C. Tsai, and W. H. Chen, "Coherence analysis between respiration and PPG Signal by bivariate AR Model,"*World Acad. Sci. Eng. Technol.*, vol. 53, pp. 847–851, 2009.
[15] K. H. Chon, S. Dash, and K. Ju, "Estimation of respiratory rate from photoplethysmogram data using time-frequency spectral estimation," *IEEE Trans. Biomed. Eng.*, vol. 56, no. 8, pp. 2054–2063, Aug. 2009.
[16] S. Dash, K. H. Shelley, D. G. Silverman, and K. H. Chon, "Estimation of respiratory rate from ECG, photoplethysmogram, and piezoelectric pulse transducer signals: A comparative study of time-frequency methods," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 5, pp. 1099–1107, May 2010.
[17] K. V. Madhav, M. R. Ram, E. H. Krishna, and K. A. Reddy, "Monitoring respiratory activity using PPG signals by order reduced-modified covariance AR technique," in *Proc. 4th IEEE iCBBE*, Chengudu, China, Jun. 18–20, 2010, pp. 1–4.
[18] J. Lee and K. H. Chon, "An autoregressive model-based particle filtering algorithms for extraction of respiratory rates as high as 90 breaths per minute from pulse oximeter," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 9, pp. 2158–2167, Sep. 2010.

[19] J. Lee and K. H. Chon, "Time-varying autoregressive model based multiple modes particle filtering algorithm for respiratory rate extraction from pulse oximeter," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 3, pp. 790–794, Mar. 2011.

[20] K. V. Madhav, M. R. Ram, E. H. Krishna, K. A. Reddy, and K. N. Reddy, "Estimation of respiration rate from principle components of photoplethysmographic signals," in *Proc. of 2010 IEEE EMBS conf. on Biomed. Eng. & Sciences, IECBES-2010*, Kuala Lumpur, Malaysia, Nov./Dec. 2010, pp. 311–314.

[21] K. V. Madhav, M. R. Ram, E. H. Krishna, K. N. Reddy, and K. A. Reddy, "Estimation of respiratory rate from ECG, BP and PPG signals using empirical mode decomposition," in *Proc. 28th IEEE I2MTC*, Hangzhou, China, May 10–12, 2011, pp. 1611–1664.

[22] K. V. Madhav, M. R. Ram, E. H. Krishna, K. N. Reddy, and K. A. Reddy, "Use of multi scale PCA for extraction of respiratory activity from photoplethy -smographic signals," in *Proc. 29th IEEE I2MTC*, Graz, Austria, May 13–16, 2012, pp. 1784–1787.

[23] K. A. Reddy, B. George, and V. J. Kumar, "Use of Fourier series analysis for motion reduction and data compression of photoplethysmographic

