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Motion Artifact Reduction in Photoplethysmographic Signals: A Review

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Abstract:

Photoplethysmography(PPG) is a simple and low-cost optical technique that can be used to detect blood volume changes in the microvascular bed of tissue. The PPG technology has been used in a wide range of commercially available medical devices for measuring oxygen saturation, blood pressure and cardiac output, assessing autonomic function and also detecting peripheral vascular disease. The recorded PPG signal acquired using PPG sensors are usually corrupted with Motion Artifacts(MA) due to the voluntary or involuntary movements of patient. The identification and elimination of MA has received much attention in the literature over recent years. This review focuses on the methods for MA reduction from corrupted PPG signals.

Key words: *PPG, Motion artifact, Adaptive Filter ,Singular Value Decomposition(SVD),Independent Component analysis(ICA),Wavelet transform.*

1.Introduction

Photoplethysmography(PPG) was first reported in 1937 by Hertzman and his colleagues[1].It is a noninvasive, electro-optic method for detecting the cardiovascular pulse wave generated by the elastic nature of the peripheral vascular arteries excited by the quasi-periodic contractions of the heart. Various noises tend to decrease the accuracy of the measured PPG signal, including respiration, motion artifacts, and external light sources. Among them, motion artifacts are the main cause of degraded accuracy[2].The PPG signal is easy to be exposed to more noise according as the medical instruments decrease in size and become portable or wearable. Especially, the frequency band of the motion artifacts overlaps that of the PPG signal .So it is difficult to remove the motion artifacts from the PPG signal.PPG signals can be used in clinical assessment such as heart rate (HR) estimations and extraction of arterial flow waveforms.

2.Pulse Oximeter

A pulse oximeter has become a standard monitor during critical care for noninvasive continuous monitoring of arterial-blood oxygen saturation.(SpO2). Apulse oximeter makes use of PPG signals acquired at red and infrared(IR) wavelengths with the help of suitable sensors attached to the finger/earlobe/toe of the subjects. A typical PPG signal contains two components. The first one is a large dc component, due to constant absorption of light when passing through the skin–tissue–bone. The second one is a small ac component, due to the component of light passing through pulsating arteries caused by the heartbeat [3]. A pulse oximeter needs Red and IR PPG signals with clearly separable dc and ac parts for error-free SpO_2 estimation.

If the peak-to-peak values of the pulsatile components of the Red and IR PPG signals are *AC*Red and *AC*IR, respectively, the "ratio of ratios" *R* is estimated [4],[5] as

$$R=\frac{AC\mathrm{Red}/DCRed}{ACIR/DCIR} \qquad (1)$$

Then, SpO_2 is computed by substituting the *R* value of (1) in an empirical linear approximate relation given by

$$SpO_2\% = (110 - 25R)\%. \qquad (2)$$

However, PPGs are usually corrupted by motion artifacts (MAs) due to voluntary or involuntary movements of the subject while acquiring the data.

3.Methods

3.1.Fourier Series Analysis

K. Ashoka Reddy et al [6] propose a novel method for removing motion artifacts from corrupted PPG signals by applying Fourier Series analysis on a cycle-by-cycle basis. Any periodic signal can be decomposed into a set of sinusoids made of a fundamental frequency and its harmonics, as described by the Fourier series [7].However, a Fourier series is applicable only to periodic signals and, hence, cannot directly be applied to a PPG signal, which is nonstationary and quasi-periodic. To overcome this problem Fourier series is applied on a cycle-by-cycle basis.

It is seen that, the first seven significant Fourier coefficients of each cycle is more than sufficient to compute and store also retains all the morphological features of the given PPG signal with an accuracy of 0.5%.It is seen that if the PPG is reconstructed from the Fourier Series coefficients of the corrupted PPG, original(artifact-free)PPG is obtained.

Experiments were carried out on ten volunteers within the age group of 21–50, four females with average age within (27 ± 6) and six males with average age within (35 ± 10). Artifacts were intentionally created, and the PPG signals were recorded with vertical, horizontal waving, and bending motions of the finger. The acquired data from the volunteers are first filtered using the Savitzky–Golay (SG) smoothing filter to remove high-frequency noise. Once the noise is removed, the proposed CFSA method is then applied, and the PPG signals (IR and red) are reconstructed cycle by cycle.

The raw PPG corrupted by motion artifacts is processed using an order 20 moving average filter and CFSA method and inferred that CFSA method performs well compared with the traditional moving average method. The values of the level of oxygen saturation in arterial blood (SpO2) are also computed using the PPG signal processed CFSA method and the deviation from the expected SpO2 value was less than ±3%.

The CFSA method is insensitive to heart rate variation introduces negligible error in the processed PPG signals due to the additional processing provides 35dB reduction of motion artifacts preserving all the morphological features of the PPG.

3.2.Periodic Moving Average Filter

Han-Wook Lee et al [8] proposes the Periodic Moving Average Filter (PMAF) to remove motion artifacts. The PMAF is based on the quasi-periodicity of the PPG signals[9]. The moving average method generally used to remove motion artifacts works well for intermittent noise, but cannot remove the motion artifact of large amplitude or one that occurs suddenly.

Fig. 1 shows the concept of the PMAF method. The PPG signal is segmented into periods, and each period is resampled with the same number of samples for each. The samples of each periods are then averaged. The resultant obtained is free from motion artifacts without degrading the PPG signal.Fig.2 shows the structure of the PMAF method.

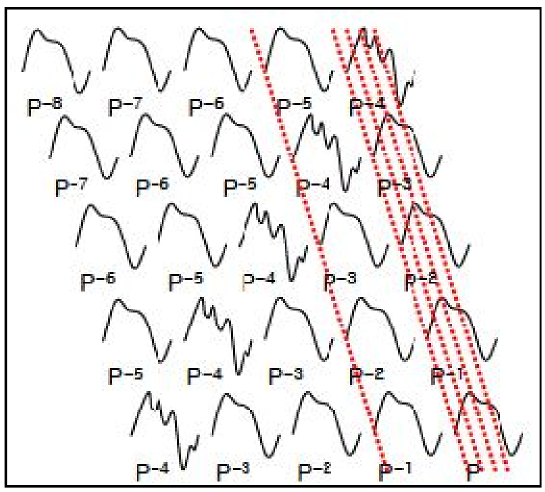


Figure 1: Concept of the PMAF method

The PMAF was simulated by using MathWorks Matlab. The PPG signal with noise is taken as the input signal and sampled at 500-Hz. After filtering the input signal the maximum and minimum values of each period is estimated. By applying the zero crossing method the means of each period were obtained from the maximum and minimum values. Interpolation or decimation was performed to ensure that each period had the same number of samples.

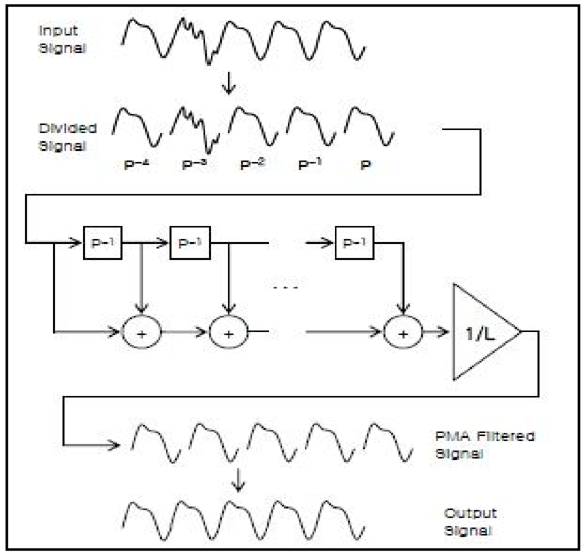
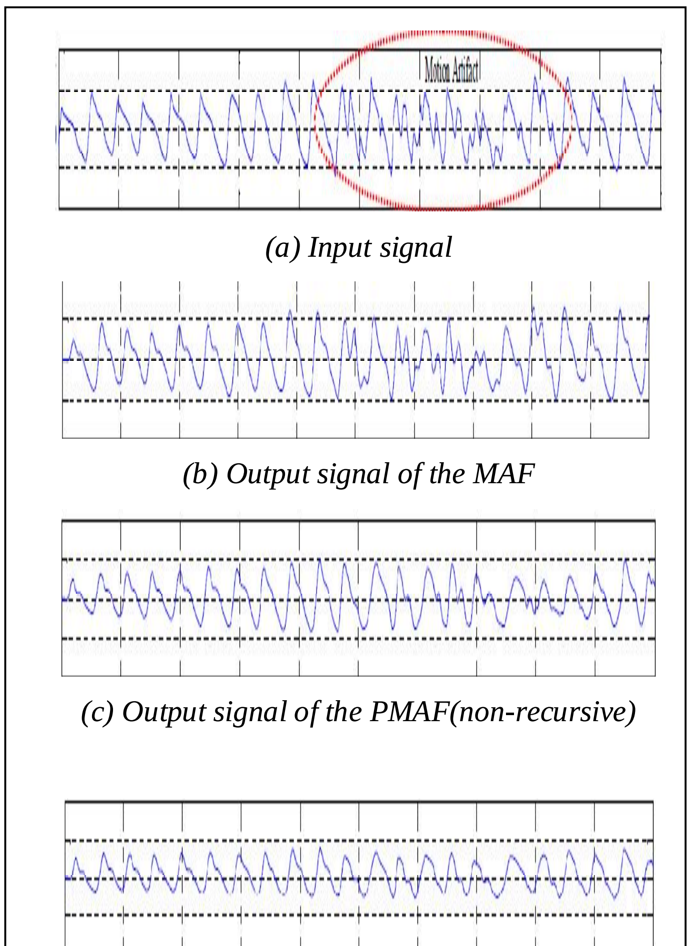


Figure 2: Structure of the PMAF method.



(a) Input signal

(b) Output signal of the MAF

(c) Output signal of the PMAF(non-recursive)

(d) Output signal of the PMAF(recursive)

Figure 3: Input signal with tap noise and the processing results

Five periods are used for the PMAF. Fig. 3 presents the results of the simulation using the input signal with the tap noise. Fig. 3(a) shows the input signal with the motion artifact Fig. 3(b) is the result of a 30th-order moving average filter (MAF). Fig. 3(c) shows the result of the PMAF non-recursive model, and Fig. 3(d) gives the result of the PMAF recursive model.

Thus PMAF method gives good results in removing motion artifacts without degrading the PPG signals.

3.3.Wavelet Denoising

Most signals are represented in the time domain. More information about the time signals can be obtained by applying signal analysis, i.e. the time signals are transformed using an analysis function. The Fourier transform is the most commonly known method to analyze a time signal for its frequency content. A relatively new analysis method is the wavelet analysis.

The wavelet analysis differs from the Fourier analysis by using short wavelets instead of long waves for the analysis function. The wavelet analysis has some major advantages over Fourier transform(FT) which makes it an interesting alternative for many applications. The analysis of a non-stationary signal using the FT or the Short Time Fourier transform(STFT) does not give satisfactory results. Better results can be obtained using wavelet analysis. One advantage of wavelet analysis is the ability to perform local analysis[10].

The continuous wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function or alternatively as shown in the following equation(11):

$$\mathrm{CWT}(a,\tau) = \frac{1}{\sqrt{a}} \int x(t) \emptyset \left[\frac{t-\tau}{a}\right] dt \qquad (3)$$

where a is the scaling factor that stretches or compresses the function, τ is the translation factor that shifts the mother wavelet along the axis, x(t) is an integral signal whose sum is to be multiplied by the translated mother wavelet denoted as φ(t) which is a function of the scaling and translation factors.

To reduce the influence of motion artifacts on heart rate(HR) and heart rate variability(HRV) C.M.Lee et al [12] proposes wavelet denoising approach for reduction of motion artifacts from photoplethysmographic recordings .Stationary wavelet transform(SWT) and wavelet transform modulus maxima (WTMM) are used to remove motion artifact.

The implementation structure for SWT is shown in Fig4, where * denotes the discrete time convolution, di are detail (wavelet) coefficients and ci are approximate (scaling) coefficients generated through the convolution chain originated from an original signal sequence c0 and level-adaptive size-varying highpass filter h1 and lowpass filter h0 respectively [13]

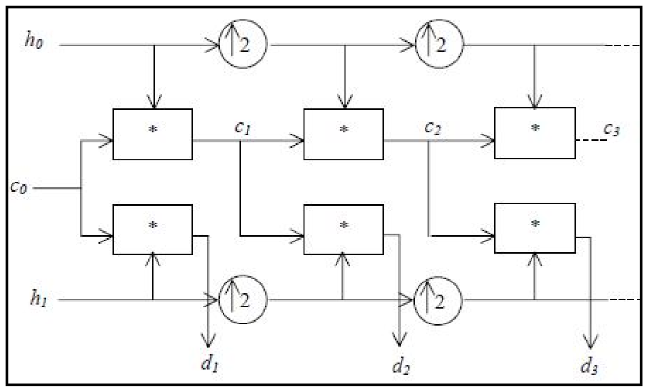


Figure 4: Three level decomposition with SWT

Two identical PPG circuits wer used one to the subjects left index finger which was held in a stable position to obtain a reference signal as standard. Meanwhile, the right index finger moved vertically or circularly to introduce motion artifact.The corrupted PPG signals were decomposed by 7-level SWT, for circular motion.For verticular motion, the signal is reconstructed by inverse of SWT and WTMM is applied to denoise the signal.By applying the proposed method there was 87% reductions in HR estimation error, 76% in HRV estimation error and 66% in instantaneous HR error for vertical motion.In circular motion, there was 61% reductions in HR estimation error, 70% in HRV estimation error and 46% in instantaneous HR error.Thus the HR and HRV estimation error can be reduced significantly using a wavelet denoising approach.

M Raghuram et al [14] used different wavelets to remove the motion artifact and their performance are evaluated.Daubechies,biorthogonal, reverse biorthogonal symlet and coiflet types of wavelets are applied for motion artifact reduction. Experimental results revealed that the SpO2 values estimated from MA reduced PPG signals by different wavelets are relatively near to each other and Daubechies wavelet exhibited superior performance over other in resorting respiratory information while removing MA.

3.4.Independent Component Analysis

To rigorously define ICA , a statistical "latent variables" model can be used[15].

xj = aj1s1+aj2s2+...+ajnsn, for all j (4)

Where x_j represents linear mixtures $x_1, ..., x_n$ of n independent components. in the ICA model, it is assumed that each mixture x_j as well as each independent component s_k is a random variable, instead of a proper time signal. The observed values $x_j(t)$, are then a sample of this random variable. Without loss of generality, it can be assumed that both the mixture variables and the independent components have zero mean: If this is not true, then the observable variables *xi* can always be centered by subtracting the sample mean, which makes the model zero-mean.

It is convenient to use vector-matrix notation . It can be denoted by **x** the random vector whose elements are the mixtures *x*1, ...,xn, and likewise by **s** the random vector with element s_1, ..., s_n. Let us denote by **A** the matrix with elements a_{ij} . Generally, bold lower case letters indicate vectors and bold upper-case letters denote matrices. All vectors are understood as column vectors; thus $\mathbf{x}^T$, or the transpose of **x**, is a row vector. Using this vector-matrix notation, the above mixing model is written as [16]

x = As (5)

The statistical model in Eq. 4 is called independent component analysis, or ICA model. The ICA model is a generative model, which means that it describes how the observed data are generated by a process of mixing the components s_i. ICA is one method, perhaps the most widely used, for performing blind source separation.

Jianchu et al [17] proposed the potential of ICA for motion artifact separation in wearable pulse oximeter signals .ICA is attractive as it does not require the prior knowledge of the system. ICA algorithms can separately address arterial and venous volume variations. Disadvantage of ICA is it assumes that all source signal component pairs are mutually independent.

Statistical relationship between motion artifacts and PPG data is studied by calculating the correlation coefficients between arterial volume variations and motion over a range of stationary to high motion conditions. Using MATLAB arterial volume variation in both stationary (Avvs) and motion conditions(Avvm) is calculated and finds the correlation between Avvs and each Avvm.

Experimental results showed that the correlation coefficient between Avvs and Avvm is less than 0.5, inferring the two are not significantly correlated. Hence, motion seriously affects arterial volume variations so, care must be taken when applying ICA to data acquired from wearable light-based sensor platforms.

Byung S.Kim et al [18] proposed that the combination of independent component analysis and block interleaving with low-pass filter can reduce the motion artifacts under the condition of general dual-wavelength measurement. To complement the popular dual-wavelength optical probe the ICA model with two independent sources is considered. Experiments with synthetic and real data proved the efficacy of the proposed algorithm.

3.5.Singular Value Decomposition

The Singular value decomposition(SVD) is an important toll of linear algebra. It is intimately related to the theory of diagonalizing a symmetric matrix. Any n x m matrix A can be written as [19]

$$A=UDV^T \tag{6}$$

Where, U = eigenvectors of AA^T(n x n),D = diag(eig(AA^T)) (n x m),V = eigenvectors of A^TA (m x m).The diagonal elements of D are called singular values. The singular values are the positive square roots of the Eigen values of A^TA. The columns of U are called the left singular vectors of A, while the columns of V are called the right singular vectors of A. The singular values of a given data matrix contains information about the noise level in the data, energy and rank of the matrix and is used for signal processing like data compression, noise removal and pattern extraction.

K. Ashoka Reddy et al [20] proposed SVD as an artifact reduction method applicable for PPG signals. Experimental results shows that SVD method preserves all the original PPG in the features of the original PPG in the processed PPG and hence extracts artifact free clean PPG signals from PPG riddled with motion artifacts. The SPO_2 estimated was also error free even when the signals are contaminated with motion artifacts.

3.6.Adaptive Filter

The basic function of a filter is to remove unwanted signals from those of interest. Obtaining the best design usually requires a priori knowledge of certain statistical parameters (such as the mean and correlation functions) within the useful signal. With this information, an optimal filter can be designed which minimizes the unwanted signals according to some statistical criterion.

One popular measure involves the minimization of the mean square of the error signal, where the error is the difference between the desired response and the actual response of the filter [21]. This minimization leads to a cost function with a uniquely defined optimum design for stationary inputs, known as a Wiener filter (Widrow and Hoff 1960). However, it is only optimum when the statistical characteristics of the input data match the a priori information from which the filter is designed, and is therefore inadequate when the statistics of the incoming signals are unknown or changing, i.e. in a nonstationary environment.

For this situation, a time-varying filter is needed to allow for these changes. An appropriate solution is an adaptive filter, which is inherently self-designing through the use of a recursive algorithm to calculate updates for the filter parameters. These updates are used to compute the taps of the new filter, the output of which is used with new input data to form the updates for the next set of parameters.

When the input signals are stationary, the algorithm will converge to the optimum solution after a number of iterations, according to the set criterion. If the signals are non-stationary then the algorithm will attempt to track the statistical changes in the input signals, the success of which depends on its inherent convergence rate versus the speed at which statistics of the input signals are changing. Fig (5) shows a block diagram of the adaptive artifact reduction scheme.

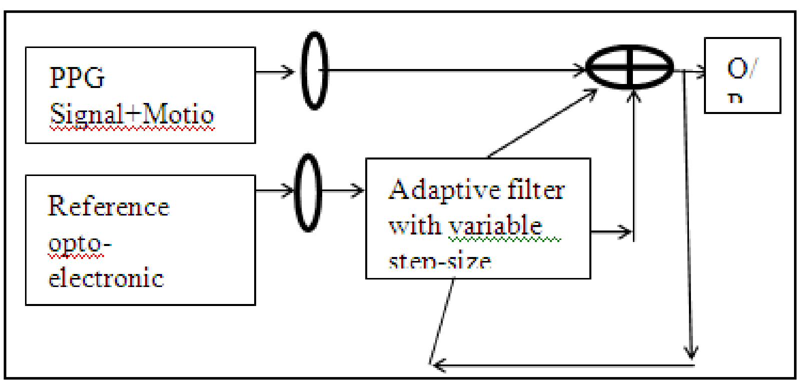


Figure 5: Block diagram of the adaptive artifact reduction scheme

The primary sensor detects the PPG signal, s(n), and additive motion artifact, vo(n), simultaneously. The reference sensor detects noise component, v1(n), which provides a correlated version of the motion artifact, vo(n) . Error signal, e(n), which is the output of the overall system, is the filtered PPG signal. With s(n) remaining constant, e(n) leads to a least mean square match to the primary signal, s(n [22]..

3.6.1.Synthetic Noise Reference Signal

M. Raghu Ram et al [23] proposed simple and efficient adaptive filtering technique for MA reduction using a synthetic noise reference signal without only extra hardware for generating the noise reference signal. It is generated from the motion corrupted signal itself. By applying LMS adaptive algorithm, MA noise is removed by estimating the synthetic noise reference signal and adapting the filter coefficients based on filter order.

3.6.2.TVS-LMS Adaptive Algorithm.

The adaptive technique developed for MA reduction can be clearly described using the block diagram in Fig(6)[24].

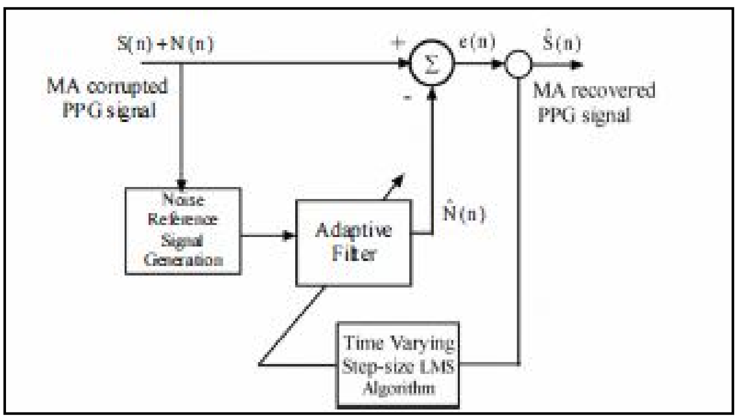


Figure 6: MA reduction using TVS-LMS adaptive technique

The MA noise is removed using TVS-LMS adaptive algorithm by estimating the noise reference signal and adapting the filter coefficients based on filter order. The TVS-LMS adaptive algorithm performed well compared to general LMS adaptive filter, as TVS-LMS algorithm has faster convergence rate.

3.6.3.AS-LMS Adaptive Algorithm

The AS-LMS based Adaptive MA reduction technique can be clearly described using the block diagram in Fig 7.[25].

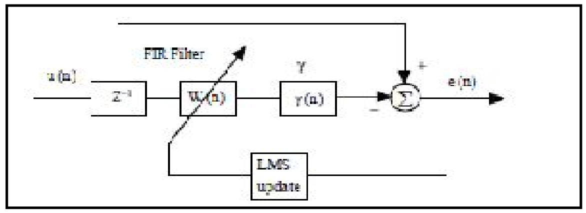


Figure 7: MA reduction using AS-LMS adaptive technique

The performance of constant step size LMS(CS-LMS), TVS-LMS and AS-LMS algorithms were evaluated and in terms of mean square error(MSE) measure with respect to the number of iterations. The performance curves clearly indicates that AS-LMS algorithm has faster convergence rate with minimum MSE.

Table[1] illustrates the figure of merit(SNR) , defined as the ratio of signal power to the generated noise reference power values for the PPGs inflicted with three different kinds of MA.

SNR Of PPG	Horizontal Motion	Vertical Motion	Bending Motion
Before Adaptive Filter	1.0745	-5.7089	-5.7414
Using CS-LMS	1.9025	-4.478	-4.2574
Using TVS-LMS	2.3897	-4.1117	-4.0517
Using AS-LMS	2.3990	-4.0012	-4.0494

Table 1: Values of SNR for MA-corrupted and MA-recovered PPG signals for different MAs

The superiority of AS-LMS is clearly evident in the table[] with high SNR values in all the cases.

4.Conclusion

Photoplethysmography has great potential for use in wide range of clinical measurements. Reliable and accurate measurement of blood oxygen saturation from commercial pulse oximeters is profoundly affected by motion artifacts(MA) introduced in to the PPG signals. In this paper different methods for reducing artifacts from a PPG signal has been discussed. SVD and CFSA methods were found to be the better methods for artifact removal compared to other methods.

5.References

1. B. Hertzman, “Photoelectric plethysmography of the fingers and toes in man,” Proc. Soc. Exp. Biol. Med., no. 37, pp. 529-534, 1937.
2. B. A. Shapiro, W. T. Peruzzi, and R. Templin, Clinical Application of Blood Gases, 5th ed., vol. 64, Mosby, St. Louis, MO, USA, 1994.
3. Y. Mendelson and B. Ochs, “Noninvasive pulse oximetry utilizing skin reflectance photoplethysmography,” IEEE Trans. Biomed. Eng., vol. 35, no. 10, pp. 798–805, Oct. 1988.
4. K. A. Reddy, “Novel methods for performance enhancement of pulse oximeters,” Ph.D. dissertation, Dept. Elect. Eng., IIT Madras, Chennai, India, 2008.
5. K. A. Reddy, B. George, N. M. Mohan, and V. J. Kumar, “A novel calibration-free method for measurement of oxygen saturation in arterial blood,” IEEE Trans. Instrum. Meas., vol. 58, no. 5, pp. 1699–1705, May 2009
6. K. Ashoka Reddy, Boby George, and V. Jagadeesh Kumar,” Use of Fourier Series Analysis for Motion Artifact Reduction and Data Compression of Photoplethysmographic Signals” IEEE Trans on Instrumentation and measurement, VOL. 58, NO. 5, MAY 2009.
7. R. N. Bracewell, The Fourier Transform and Its Applications, 3rd ed. New York: McGraw-Hill, 2000
8. Han-Wook Lee, Ju-Won Lee, Won-Geun Jung, and Gun-Ki Lee” The Periodic Moving Average Filter for Removing Motion Artifacts from PPG Signals”International Journal of Control, Automation, and Systems, vol. 5, no. 6, pp. 701-706, December 2007
9. P. E. McSharry, G. D. Clifford, L. Tarassenko, and L. A. Smith, “A dynamical model for generating synthetic electrocardiogram signals,”IEEE Trans. Biomed. Eng., vol. 50, no. 3, pp. 289-294, 2003.
10. S. Hans-Gorge, "Wavelets and signal processing; an application-based introduction," Newyork: Springer, 2005.
11. M Raghuram, K. Venu Madhavi, E. Hari Krishna, and K. Ashoka Reddy Evaluation of Wavelets for Reduction of Motion Artifacts in Photo plethysmographic Signals 10th International Conference on Information Science, Signal Processing and their Applications (ISSPA 2010).

12. C. M. Lee and Y. T. Zhang Reduction of Motion Artifacts from Photoplethysmographic Recordings Using a Wavelet Denoising Approach ,"IEEE Trans. Biomed. Eng., vol. 50, no. 3, pp194-195, 2003.
13. G. P. Nason and B. W. Silverman, 'The stationrtry wavelet transform and some statistic application," Lecrirre Notes in Srarisrics, 103; pp. '281-299. 1995.
14. M Raghuram, K. Venu Madhavi, E. Hari Krishna, and K. Ashoka Reddy " Evaluation of Wavelets for Reduction of Motion Artifacts in Photo plethysmographic Signals", 10th International Conference on Information Science, Signal Processing and their Applications (ISSPA 2010).
15. A.Hyvrinen, J. Karhunen, and E. Oja," Independent Component Analysis." New York: Wiley, 2001.
16. D. F. Elliot, Handbook of Digital Signal Processing Engineering Applications. New York: Academic, 1987.
17. Jianchu Yao and Steve Warren ," A Short Study to Assess the Potential of Independent Component Analysis for Motion Artifact Separation in Wearable Pulse Oximeter Signals Proceedings" of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference Shanghai, China, September 1-4, 3585-3588 , 2005
18. Byung S. Kim and Sun K. Yoo ," Motion Artifact Reduction in Photoplethysmography Using Independent Component Analysis ", IEEE transactions on biomedical engineering, vol.53,no.3,2006.
19. V. C. Klema and A. J. Laub, "The singular value decomposition: Its computation and some applications," IEEE Trans. Autom. Control., vol. AC-25, no. 2, pp. 164-176, 1980.
20. K. Ashoka Reddy and V. Jagadeesh Kumar "Motion Artifact Reduction in Photoplethysmographic Signals using Singular Value Decomposition", Instrumentation and Measurement Technology Conference - IMTC 2007 Warsaw, Poland, May 1-3, 2007 Haykin, **S.,** Adaptive Filter Theory, Third Edition. 1996.
21. Clarkson, P.M., Optimal and Adaptive Signal Processing. 1993.
22. M. R. Ram, K. V. Madhav, E. H. Krishna, K. N. Reddy, and K. A. Reddy, "Adaptive reduction ofmotion artifacts from PPG signals using a synthetic noise reference signal," in Proc. IEEE EMBS Conf. Biomed. Eng. Sci., Nov./Dec. 2010, pp. 315–319.

23. M. R. Ram, K. V. Madhav, E. H. Krishna, K. N. Reddy, and K. A. Reddy, "On the performance of time varying step-size least mean squares (TVSLMS) adaptive filter for MA reduction from PPG signals," in Proc. IEEE Int. Conf. Commun. Signal Process., Feb. 2011, pp. 431–435.
24. M. R. Ram, K. V. Madhav, E. H. Krishna, K. N. Reddy, and K. A. Reddy, "On the performance of AS-LMS based adaptive filter for reduction of motion artifacts from PPG signals," in Proc. 28th I2MTC, Hangzhou, China, May 10–12, 2011, pp. 1536–1539.
25. E. N. Bruce, Biomedical Signal Processing and Signal Modeling. New York: Wiley, 2001.
26. J. G. Webster, Design of Pulse Oximeters. New York: Taylor & Francis, 1997.
27. T. L. Rusch, R. Sankar, and J. E. Scharf, "Signal processing methods for pulse oximetry," Comput. Biol. Med., vol. 26, no. 2, pp. 143–159, Mar. 1996.
28. A.B. Barreto, L. M. Vicente, and I. K. Persad, "Adaptive cancellation of motion artifact in photoplethysmographic blood volume pulse measurements for exercise evaluation," in Proc. IEEE-EMBC/CMBEC, Sep. 20–23, 1995, vol. 2, pp. 983–984.
29. A.R. Relente and L. G. Sison, "Characterization and adaptive filtering of motion artifacts in pulse oximetry using accelerometers," in Proc. Conf. EMBS/BMES, Houston, USA, Oct. 23–26, 2002, pp. 1769–1770.