Motion Artifact Reduction from PPG Signals During Intense Exercise Using Filtered X-LMS

Khawaja Taimoor Tanweer[1],Syed Rafay Hasan[2] and Awais Mehmood Kamboh[*]
National University of Sciences and Technology, Islamabad, Pakistan[1,*], Tennessee Tech University, Tennessee, USA[2]
Email: (13mseektanweer, awais.kamboh)@seecs.edu.pk[1,*],shasan@tntech.edu[2]

***Abstract*—Photoplethysomographic (PPG) signal is crucial for non-invasive monitoring of heart rate. It is acquired by using pulse oximeter that are prone to artifacts. A major application of this technique is monitoring the heart rate during physical exertion. Extraction of heart rate (HR) from the PPG in this case is difficult due to the strong motion related artifacts. This paper proposes an efficient method based on a reference generation using singular value decomposition and then multistage application of filtered X-LMS for removing motion artifacts from PPG signal. Simultaneous three-axis acceleration data is acquired and used as reference signal to measure time and extent of motion artifact in PPG signal. This is followed by an application of Slope Sum Method (SSM) to track peaks, and thus determine the heart rate. Testing of proposed method on PPG signals acquired from multiple subjects performing intense exercises (jogging at an average speed of 12 km/hour), results in mean absolute error of 1.37 beats per minute (BPM). Moreover, it is shown that proposed algorithm is robust to excessive occurrence of motion artifacts.**

***Index Terms*—Photoplethysomography, Adaptive Filters, Slope Sum Method, Spectrum Estimation, Peak Tracking, blood oxygen saturation SpO_2, motion artifact**

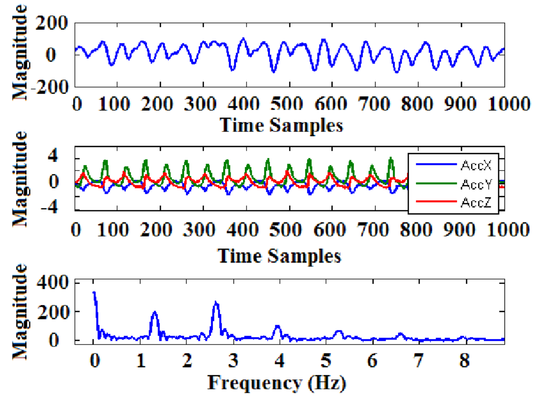

Fig. 1: (a) PPG Signal influenced by Motion Artifact, (b) Simultaneous accelerometer data, and (c) Spectra of MA corrupted PPG signal

I. Introduction

Photoplethysmographic (PPG) signals are one of the important physiological signals for measuring oxygen carrying haemoglobin level in blood and Heart Rate(HR) [1].For acquiring these signals, the most simple, cost effective and extensively used non invasive technique is pulse oximetry. By using this technique, PPG signals are obtained by using a small wearable device which can be adjusted either on finger tips or on the forehead. LED light of certain wavelength is illuminated on one side of the wearers finger. As the light passes through the finger, some of it is absorbed in the skin tissues while the remaining is detected by a sensor on the other end of the device. As the absorbed light's intensity is dependent on the blood flow. The volume of blood in the arteries changes with the heart pulse, hence the light detected by the sensor also varies resulting in a periodic signal that is used to measure HR. As PPG signals are highly prone to motion artifact due to body movement, so even a slightest change detected by these devices can distort the PPG signal which affects HR information [2] as shown in Fig. 1.

To detect and remove small motion artifacts, several signal processing algorithms are used in which finger movements or slight changes in body posture are registered [3][4].Similarly, Ram *et* al in [3] employed adaptive noise filtering algorithm for removing motion artifact, but it is dependent on the choice of reference signal. Independent component analysis by Schaeck in [5] is also effective in removing motion artifact. Apart from monitoring patients HR, wrist-type PPG signals are also used for measuring Heart Rate HR and amount of oxygen in blood SpO_2 during intensive physical exercise which is of great interest to wearable smart devices i.e. phone, watches [2]. All the above mentioned methods are useful but they have some other disadvantage i.e. time and computational cost, multiple assumptions in removing small motion artifacts. The purpose of this research is to provide an efficient method of removing motion artifacts, in which simultaneous three-axis acceleration data is acquired and used for measuring time and extent of motion artifact in PPG signal and effectively monitor HR during intense exercise (12-15 km/hr) i.e. running by the subject. The reference signal defining motion artifact components are used in adaptive noise cancellation step for removing motion artifact from the raw PPG signal. In the end, slope sum method (SSM) is used as a tracking algorithm for heart rate.

We present an approach that proposes an efficient method based on reference generation using singular value decomposition and then application of filtered X-LMS for removing motion artifacts. Our scheme is analyzed by 1) Comparing performance of MA reduction technique using different variants of LMS i.e. Filtered X-LMS, Normalized LMS, Delayed LMS and Adjoint LMS. 2) Computing heart rate of PPG signal and then comparing performance measures i.e. average percentage error, Pearson correlation.

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II. THEORY

The proposed technique consist of multiple successive stages of artifact reduction i.e. LMS adaptive filtering. After artifact removal, SSM is used for peak detection and tracking. Overall proposed technique displaying multiple processing blocks is shown in Fig. 2.

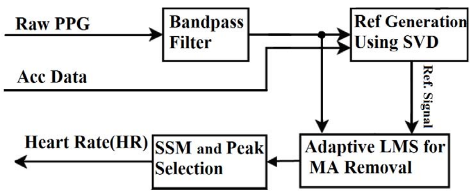

Fig. 2: Flow Diagram Showing Processing Blocks of Proposed Technique

A. Out-Band MA Removal

As useful PPG band lies between 0.3-5 Hz, so for attenuating frequencies outside this band, 4th order butterworth IIR band pass filter is used. This results in removal of out-band noise from the PPG signal i.e. 50Hz AC noise, muscle contraction noise, and any other electrical interference.

B. Singular value Decomposition (SVD)

Providing motion data to filtering block without extracting relevant band motion data will result in divergence of LMS filter [2]. So we have used SVD as our tool for generation of motion artifact (MA) reference for adaptive filtering step. As noisy components of the raw PPG signal are correlated with the motion accelerometer data. So first it is necessary to extract PPG band motion artifact components from accelerometer data. In [2], the singular value decomposition was utilized and its effectiveness was established for the required purpose. Those components of the frequency which are in PPG signal frequency band are used to generate motion artifact reference signal for the filtering step. For generating motion reference, four steps includes ; embedding and singular value decomposition which are followed by grouping and reconstruction using [2]. Reference signals corresponding to 0.4-5 Hz band are extracted and used in the adaptive filtering process.

C. In-Band MA Removal

LMS adaptive filters work on the principle of stochastic gradient descent in which filters coefficients $h(n)$ are updated based on the least mean error $e(n)$ at current time. The desired reference signal, generated in step II-B, is used as the noise reference for filtering purposes. Standard LMS algorithm [6] summary is shown in equation (1):

$$\begin{aligned} u(n) &= [u(n), u(n-1)....u(n-m+1)]^T \\ e(n) &= d(n) - h^H(n).u(n) \\ h(n+1) &= h(n) + \mu.e^*(n).u(n) \end{aligned} \tag{1}$$

where $u(n)$, $d(n)$ and $e(n)$ are input, desired output and error induced signal respectively. whereas $h(n)$ are the weights of the estimated filter and μ defines step size to be utilized in the adaptive filter. Whereas step size μ describes how adaptive filter converges which depends on weight adjustments. If a larger μ is selected, gradient depending on weights will result in high amplitude oscillations about the optimal value, that can result in larger mean square error and less accuracy is achieved and vice-versa. So trade off between the two outcome ensues. Different techniques of LMS adaptive filters are used for the purpose i.e. normalized LMS, Filtered X-LMS, delayed LMS and adjoint LMS.

Due to slow convergence rate and dependence of LMS algorithm on input scaling factors, choosing learning rate turns out to be a problem due to stability issues [6]. The **Normalized LMS (NLMS)** normalizes power of the input signal hence solves the problem incurred in standard LMS [6]. To improve convergence rate another type of LMS is introduced known as **Delayed LMS**. To implement fast adaptive filter, multiple delays are introduced in algorithm for pipelining which results in faster processing [7]. In **Adjoint LMS**, error signal is used instead of the primary input signal. This error signal is filtered using adjoint filter of the error channel. This technique proves very much useful when it comes to multiple input multiple output (MIMO) systems.

Due to usage of filter in the error path, performance of LMS filter drastically decreases as it results in low convergence rate and unstable algorithm. We have seen in section II-C that standard LMS is based on steepest descent algorithm. It does not have a secondary path therefore precise noise free signal is not possible to generate. However, addition of secondary path results in slow convergence, hence computational complexity remains the same. A compensated algorithm has been proposed in [8] to estimate the secondary path. An identical filter has been placed in-line with reference signal path for adjusting weights of the filtering algorithm. This adjusted algorithm is called **Filtered X-LMS** algorithm. Coefficients of the compensation filter are estimated by using a random PPG signal with minimum unwanted noise. Fig. 3 shows the working of filtered x-algorithm whereas equation (2) shows algorithm in mathematical form [8] as follow:

$$\begin{aligned} y_C(n) &= w^T(n).u(n) : \text{Output generation} \\ e(n) &= d(n)y_C(n) : \text{Error calculation} \\ u_{C^*}(n) &= \sum_{i=0}^{I-1} c_i^*.u(n-i-M+1) \\ w(n+1) &= w(n) + \mu.u_{C^*}(n)e(n) : \text{Weight update} \end{aligned} \tag{2}$$

In this equation, c_i^* represents coefficients of estimated filter for compensation. Now convergence and stability are both influenced by the reference signal $u_{C^*}(n)$ along with some delay introduced which corresponds to both forward paths [9].One of these variants of LMS filter is utilized for the adaptive filtering block shown in Fig.2.

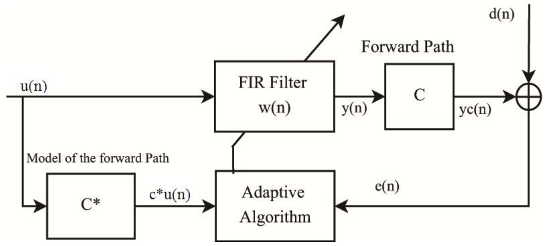

Fig. 3: Active Noise Control using Filtered X-LMS [8]

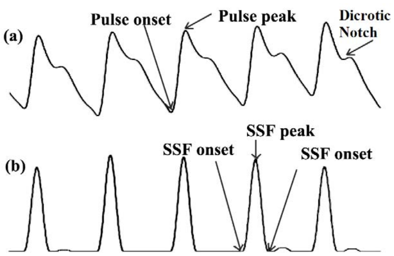

Fig. 4: Relation between PPG signal and SSM generated signal [10] (a) Raw PPG signal, (b) SSM signal

D. SSM Peak Tracking

The Slope Sum Method is used to improve the upslope or ascending part of PPG signal while it decreases dicrotic notch of that signal. A signal is transformed into SSM signal for detecting peaks and then tracking using adaptive methods. The offset and onset of a signal are localized within the given window range. Finally peaks are identified based on onset and offset of a signal. Slope sum method as a function of time t is given by:

$$SSM_t = \sum_{k=t-w}^{t} \triangle u_k \tag{3}$$

$$\triangle u_k = \begin{cases} \triangle x_k & : \triangle x_k > 0 \\ 0 & : \triangle x_k \leq 0 \end{cases} \tag{4}$$

Where w is the length of selected window, u_k is the output of the low pass filter. A window of 2-3 seconds is used for peak tracking. Initially when the subject is at rest, maximum peak value of heart beat is measured. This value is used for estimating initial thresholding value that will be 70-80% of the maximum heart rate measured. [10]. Using initial threshold value, upcoming window peaks are estimated using adaptive thresholding technique. Threshold value is updated every time a window is updated and peak estimation continues till the signal ends. In the case of missing peaks ,few previous values are also saved which helps in estimating peak value of the next or missing window. Relation between PPG and SSM generated signal is shown in Fig. 4.

III. Experimental Setup

Dual channel PPG signal along with three-axis accelerometer data is acquired from a wrist type pulse oximeter with a sampling rate of 125 Hz [2]. For measuring heart rate one channel PPG is required so either one of red or IIR PPG channel is used. Dataset from 12 different subjects is acquired containing various degree of motion artifacts i.e intense exercises with running upto 12-15km/h. For processing each window, frame of 8-sec is selected containing 1000 samples. Bandpass filtering is applied for removing out-band MA noise from the raw signal and then reference generated by SVD is used in adaptive filtering process. Adaptive filters mentioned in Section II are used for noise cancellation with filter order 20. In the end, SSM is used for measuring heart rate of artifact reduced signal using adaptive method as discussed in Section II-D.

IV. Results and Discussion

Graphical results after applying proposed method for artifact removal and heart rate tracking are shown in Fig. 5. As ECG sensors are used for measuring HR simultaneously, it is used as a ground truth for comparing result with that of estimated heart rate. The ground truth and output filtered signals are shown as black solid line and colored solid lines, respectively. It can be seen in Fig. 5 that the proposed method has numerous advantages over other LMS schemes: 1) it removes motion artifact from the noisy signal effectively and 2) it does not affect the appearance of raw signal. Various quantitative measures are used for comparison as shown in Table II i.e. Average Percentage Error (APE), Estimation Variance (EV) with Pearson correlation (PC) and Average Absolute Error (AAE).

On applying proposed method for different step size i.e. 0.001, 0.002, 0.003, 0.005, 0.008 and 0.01 satisfactory results are obtained. Mean absolute error on all subjects are calculated and for $\mu = 0.001$ minimum value is obtained. It is observed that algorithm outcomes with an overall average absolute error of 1.37 BPM for all subjects. Overall tracking result obtained from standard LMS is satisfactory but it can be seen in Fig. 5 and Table. I that filteredX LMS has performed better than standard LMS. For standard LMS, $\text{AAE}_{\mu\,=\,0.001} < \text{AAE}_{\mu\,=\,0.003}$ as misjudgments decreases with decreasing step size. This is also due to the reason that length of adaptation time increases as system is dominated over by slower convergence modes. On comparing $\text{AAE}_{LMS} > \text{AAE}_{filt\,-\,XLMS}$. For normalized-LMS steady state error is too large to converge it to the optimal value so average absolute error is mostly in unstable range. Also due to steady state noise in adjoint and delayed LMS, instability results in larger AAE compared to filtered X-LMS. Absence of transfer function following the adaptive filter results in stability issues which filtered-X LMS has coped with. Thus minimum AAE is obtained among the other LMS techniques as seen in Table. I which shows overall tracking result obtained from filtered X LMS are best among other LMS variants.

Table III compares AAE of proposed technique with different state-of-the-art techniques. It can be seen that overall AAE of 1.37 has been obtained using proposed method. Techniques proposed in [2] and [11] are dependent on heuristic methods. As in [11] multiple parameters are required for increased performance of the system but its not possible when

TABLE I: Multiple Dataset Recordings showing Average Absolute Error. Results Were Obtained After Application Of Each LMS Technique For Our Best Selected Step Size μ = 0.001

Method	Sub 1	Sub 2	Sub 3	Sub 4	Sub 5	Sub 6	Sub 7	Sub 8	Sub 9	Sub 10	Sub 11	Sub 12	Mean
Filt.X-LMS	1.5054	1.3300	0.9846	1.3422	0.9697	1.3108	1.3682	0.5859	0.7000	3.7100	1.2270	1.4698	1.37
D-LMS	52.5645	31.4502	0.8174	1.3632	0.9306	1.3316	1.5436	0.6180	0.6781	77.7904	1.4172	1.2802	14.31
LMS	1.7680	4.3198	1.2263	1.4422	1.4830	2.9081	4.3102	0.5953	0.6272	17.9194	4.5740	1.4636	3.55
N-LMS	48.4127	28.9163	1.2257	1.7047	1.4929	14.9514	1.6299	50.8368	1.5828	77.7076	1.4854	1.8233	19.31
Adj-LMS	53.9424	41.5539	0.7889	1.5007	0.9703	1.2926	1.4680	0.5716	0.6756	77.0987	1.3441	1.4077	15.21

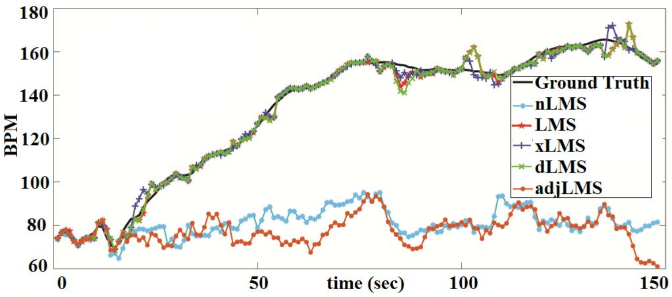

Fig. 5: Comparison of ground truth BPM vs obtained BPM using various LMS techniques

TABLE II: Performance Measures obtained using different LMS techniques for Subject 1

Method	LMS	FiltXLMS	DLMS	NLMS	AdjLMS
AEE	1.7680	1.5054	52.5645	48.41	53.94
AEP	0.0142	0.0122	0.375	0.354	0.3835
EV	7.3518	5.1395	792.4	639.3720	836.8900
PC	0.9968	0.9978	0.301	0.2798	0.3122

TABLE III: Average absolute error of proposed method vs state-of-the-art technique

Subject	TROIKA [2]	JOSS [11]	MICROST [12]	Proposed Method
1	2.29	1.33	2.9	1.5054
2	2.19	1.75	3.05	1.3300
3	2.00	1.47	2.03	0.9846
4	2.15	1.48	2.29	1.3422
5	2.01	0.69	2.64	0.9697
6	2.76	1.32	2.58	1.3108
7	1.67	0.71	1.97	1.3682
8	1.93	0.56	1.77	0.5859
9	1.86	0.49	1.87	0.7000
10	4.7	3.81	3.81	3.7100
11	1.72	0.78	1.91	1.2270
12	2.84	1.04	4.07	1.4698
Average	2.34	1.29	2.58	1.37

generalization of the algorithm is required. In our case only few parameters are required such as filter order, window size and step size for adaptive filtering process. Also when intense motion is performed, it influences heart rate which invalidates the assumption of statistical independence between PPG and accelerometer signal in [2].

V. Conclusions

In this paper, we proposed an efficient method for removing motion artifact and estimating heart rate from physiological signal during variable intense exercises. PPG signal is acquired along with simultaneous three-axis acceleration data for reference generation for noise cancellation technique. Different variants of LMS filters are used for motion artifact reduction. In the end, SSM is used for detecting and estimating heart rate. Heart rate values estimated from proposed method using filtered X-LMS are pretty much close to ground values. Hence it is suitable for estimating heart rates during excessive physical exercise. Also filtered X-LMS has never been used before for reducing motion artifact from PPG signal, this work could create new horizon in artifact reduction based problems.

References

[1] J. Allen, "Photoplethysmography and its application in clinical physiological measurement," *Physiological Measurement*, vol. 28, no. 3, p. R1, 2007. [Online]. Available: http://stacks.iop.org/0967-3334/28/i=3/a=R01

[2] Z. Zhang, Z. Pi, and B. Liu, "Troika: A general framework for heart rate monitoring using wrist-type photoplethysmographic signals during intensive physical exercise," *IEEE Transactions on Biomedical Engineering*, vol. 62, no. 2, pp. 522–531, Feb 2015.

[3] M. R. Ram, K. V. Madhav, E. H. Krishna, N. R. Komalla, and K. A. Reddy, "A novel approach for motion artifact reduction in ppg signals based on as-lms adaptive filter," *IEEE Transactions on Instrumentation and Measurement*, vol. 61, no. 5, pp. 1445–1457, May 2012.

[4] A. Wood, *Physiology, Biophysics, and Biomedical Engineering*, ser. Series in Medical Physics and Biomedical Engineering. CRC Press, 2016. [Online]. Available: https://books.google.com.pk/books?id=V0fSBQAAQBAJ

[5] T. Schck, C. Sledz, M. Muma, and A. M. Zoubir, "A new method for heart rate monitoring during physical exercise using photoplethysmographic signals," in *2015 23rd European Signal Processing Conference (EUSIPCO)*, Aug 2015, pp. 2666–2670.

[6] S. Haykin, *Adaptive Filter Theory (3rd Ed.)*. Upper Saddle River, NJ, USA: Prentice-Hall, Inc., 1996.

[7] H. T. Huynh, P. Fortier, and J. Martinet, "Generalized dlms algorithm," in *Communications, Computers and Signal Processing, 1997. 10 Years PACRIM 1987-1997 - Networking the Pacific Rim. 1997 IEEE Pacific Rim Conference on*, vol. 1, Aug 1997, pp. 448–452 vol.1.

[8] L. Håkansson, I. Claesson, and P.-O. Sturesson, "Adaptive feedback control of machine-tool vibration based on the filtered-x lms-algorithm," *Journal of low frequency noise, vibration and active control*, vol. 17, no. 4, pp. 199–213, 1998.

[9] A. Uncini, *Fundamentals of Adaptive Signal Processing*, ser. Signals and Communication Technology. Springer International Publishing, 2014. [Online]. Available: https://books.google.com.pk/books?id=T18EBgAAQBAJ

[10] D. G. Jang, U. Farooq, S. H. Park, and M. Hahn, "A robust method for pulse peak determination in a digital volume pulse waveform with a wandering baseline," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 8, no. 5, pp. 729–737, Oct 2014.

[11] Z. Zhang, "Photoplethysmography-based heart rate monitoring in physical activities via joint sparse spectrum reconstruction," *IEEE Transactions on Biomedical Engineering*, vol. 62, no. 8, pp. 1902–1910, Aug 2015.

[12] S. Zhu, K. Tan, X. Zhang, Z. Liu, and B. Liu, "Microst: A mixed approach for heart rate monitoring during intensive physical exercise using wrist-type ppg signals," in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Aug 2015, pp. 2347–2350.