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A Review of Signal Processing Algorithms for Monitoring Heart Rate from Motion Corrupted Photo Plethysmo Graphic Signals

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Abstract: Heart rate monitoring for fitness applications has gained new aspects with the emerging of smart watches or wrist bands. Estimating heart rate from motion corrupted Photo Plethysmo Graphic (PPG) signals is extremely difficult under intensive physical exercise. Removing motion artifacts (MA) from the PPG signal is one of the most challenging issues. In this paper, a survey of methodologies for heart rate estimation from motion corrupted PPG signals is presented. Various MA removals, heart rate spectrum estimation from cleansed PPG signal and spectral peak tracking methods are discussed. Challenges associated with heart rate estimation from motion corrupted PPG signalsfor each method are studied and enabling solutions are reviewed.

Keywords: Photoplethysmography (PPG), Heart Rate Monitoring, Motion artifact (MA),

I. INTRODUCTION

Photo Plethysmo Graphic (PPG) signals [1], [2] are becoming popular means of heart rate monitoring due to their wearable implementation rather than conventional electro cardiogram technology which uses ground sensors and reference sensors for heart rate monitoring. Although heart rate monitoring is traditionally carried out for clinical applications, when fitness applications are considered, it involves obtaining the nearly accurate heart rate values from highly artifact contaminated PPG signals.

The PPG signals are obtained using pulse oximeter which is embedded in a small wearable device. Pulse oximeter contains LED and photo detector which are used to cast the light to the wearer's skin and to obtain the transmitted or reflected light respectively. The intensity of light depends on the amount of blood in the arteries which helps to track the cardiac rhythm and hence heart rate. Different types of wearable sensor such as wrist, ear lobe or fingertip type devices are used for different scenarios. Fingertip or ear lobe sensors can provide nearly accurate values of heart rate in clinical scenarios where the patient is in rest or performing small physical movements. At its emergence even small movements performed by the patient caused significant distortion in the acquired signal.

Wrist type sensors are mainly meant for fitness applications where the subject is performing various physical exercises. Wrist type devices provide immediate feedback on how hard the subject is working out so that adjustments can be made to get the greatest benefit from exercise regimen. The goal is to exercise within target heart rate zone for maximum impact. For moderate-intensity physical activity a person's target heart rate should be 50 % to 70 % of his or her maximum heart rate. Because of its wearable nature wrist type sensors enhances user experience. But MA affects the PPG signal much adversely in this type of devices due to the increased flexibility of wrist compared to fingertip or earlobe. Hand movements enlarge the gap between sensor and skin causing the light to be leaked. This is the main reason for MA in PPG signal acquired by wrist type sensor. However designing wrist type wearable sensors increases user experience by indicating the heart rate at current instant while performing intensive physical exercise. Also this type of sensors is very useful for real time mobile surveillance of heart rate of elderly people. Since the effect of motion artifacts is very strong compared to other type of sensors such as ear lobe or fingertip type sensors, it requires stronger and efficient signal processing algorithms.

In this paper various algorithms used for obtaining the artifact free PPG signal and algorithms for estimating heart rate are reviewed. Starting from the algorithms used for low movement scenario algorithms that can be used for intensive motion is also described.

Paper is organized as following sections. Section II contains various challenges faced in HR monitoring from motion corrupted PPG signals. Section III gives detailed description about various MA removal techniques. Section IV describes spectral analysis. Conclusion is given in the last section.

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II. CHALLENGES

HR monitoring from motion corrupted PPG signals becomes ill posed because of various reasons. Khan et al. describes some important challenges for monitoring HR from PPG signals with significant motion artifacts [3].Low movement scenarios such as clinical applications are not concerned here since the effect of MA is very less compared to high movement scenario such as fitness applications.

Because of the increased flexibility of hand compared to other body parts such as earlobe or fingertip the gap between the skin sensor interface increases or changes while the subject is performing intensive physical exercise. This causes significant variations in the intensity of measured PPG signal. As a result the periodogram of the PPG signal contains large spurious MA peaks near to the HR peak. To show the impact of different type of problems first ECG signal and corresponding PPG signals are shown in Fig 1(a). The effect of loose contact as described above is shown in Fig 1 (b).

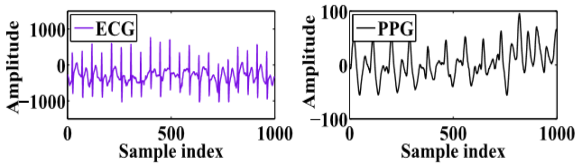

Fig. 1(a). ECG and corresponding PPG signals

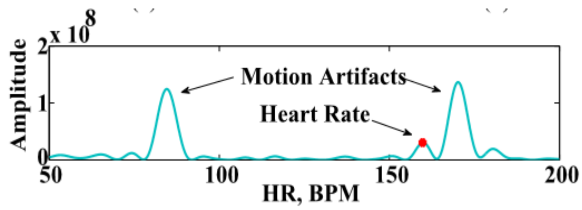

Fig. 1 (b).Periodogram of PPG signal

The second important challenge in HR estimation is that due to the exhaustive hand movement position of sensors becomes far apart from skin. This may last for some seconds. Because of this, the peak corresponding to HR might be totally absent in the spectrum. This effect can be shown in the periodogram of the MA corrupted PPG signal. Periodogram along with the corresponding ECG and PPG are shown in Fig. 2 (a) and (b) respectively.

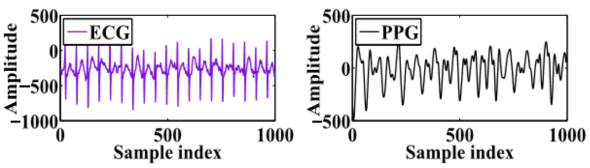

Fig 2 (a). ECG and corresponding PPG signal segments

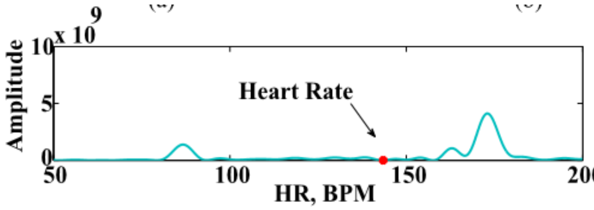

Fig 2 (b) Periodogram of the PPG signal.

Third problem is that the MA may be periodic or aperiodic. It depends on the nature of physical movement. MA is aperiodic in the case of random hand movement or while performing exercises like boxing or weight lifting. However periodic hand swing during running exercise causes the MA periodic. HR can be considered as periodic for small time windows so it contains higher order harmonics. The presence of this higher order harmonics is not sufficient to extract HR from MA corrupted PPG signals since MA can be of periodic or aperiodic.

Another problem is that the MA peak may be so close to the HR peak, so for a given resolution they may get indistinguishable. This is shown in Fig 3 (a) and (b). Fig3 (a) shows the ECG and corresponding PPG signals and (b) shows periodogram. Sometimes the strongside lobes of MA mask HR peak in spectrum.

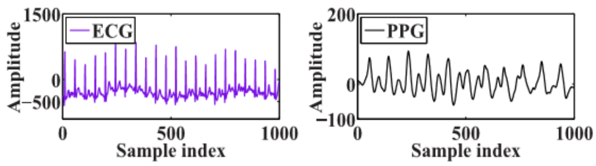

Fig. 3(a). ECG and corresponding PPG signals

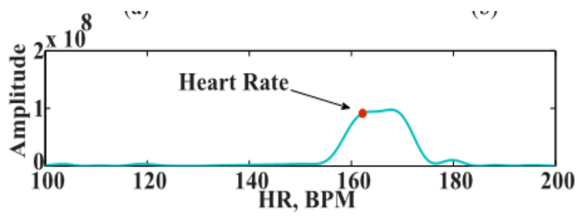

Fig. 3(b).Periodogram of PPG signal

Other important thing is that estimation of heart rate becomes difficult or there occurs error when the subject is taking rest after exercise or when changing speed suddenly [22]. During steady exercise HR and MA peaks keep a particular pattern in spectra. This is destroyed when a sudden change in speed occurs or when the subject comes to rest.

Finally HR monitoring also suffers from runaway error. Sometimes HR tracking algorithm loses track of monitoring HR.in some time windows MA peak will be so close to the HR peak and mistakenly corresponding frequency bin is selected as HR. In successive time

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windows HR tracking mechanism keep following MA peaks. This is called runaway error.Khan et al proposed an algorithm to avoid runaway error.

III.MA REMOVAL ALGORITHMS

Removal of motion artifacts or noise cancellation is the first and one of the important step in HR monitoring.MA are caused due to different reasons such as non-periodic and intensive hand movements, loose contact between skin and wrist band. In early stages PPG signals were mainly used for health monitoring in hospital beds. In that situation even small motions performed by patient caused significant distortion in monitoring of HR. Algorithms that developed in early stages are mainly to tolerate this kind of low movements.

Such algorithms include AS-LMS filter, empirical mode decomposition (EMD), constraint independent component analysis (CICA) etc. Though these algorithms performed well for clinical applications, applying it for fitness applications didn't yield good results. To tolerate with intensive hand motions algorithms such as TROIKA, JOSS, GRESS etc. proposed recently.These techniques use different methods for MA removal, like SSA (Sparse Spectrum Analysis), MMV (Multiple Measurement Vector) method and gridless spectrum estimation for MA removal. Other recent method also uses Wiener filtering with phase vocoder,Kalman filtering, EnsembleEmpirical Mode Decomposition (EEMD) with Absolute Criterion (AC), Discrete Wavelet Transform (DWT) etc. First algorithms used for low movement scenario are described and then those for the intensive movement.

A. Periodic moving average filter (PMAF)

Removal of in-band frequency components in the noisy PPG signal is difficult. PMAF exploits the quasi-periodic nature of PPG signals for noise cancellation. Lee et al. proposed a noise removal algorithm for PPG signals based on PMAF [5]. In that method PPG signal is divided into periodic segments and each segment is averaged to get noise free PPG signal

B. Adaptive noise cancellation

In the early stages of the technology, PPG signals are mainly exploited to monitor the HR of patients in hospital beds where the physical motion is very limited. Those sensors are earlobe or fingertip type. Even in those scenarios small motion performed by the finger or earlobe caused significant distortion in the acquired PPG signals. So for removing this artifactadditional hardware was required. This additional hardware used to generate a reference signal which can be employed to remove MA from PPG signals. However, by eliminating the use of additional hardware reduces cost and computational complexity of system. This can be implemented using an adaptive filter with a reference signal which is derived from motion corrupted PPG signals. The system can remove in band MA components. Ram et al. [6] used an Adaptive Step size Least Mean Square (AS-LMS) filter to remove MA. In that method reference signal was generated by using Fast Fourier Transform (FFT), Independent Component Analysis (ICA) or Singular Value Decomposition (SVD). FFT method removes the out-band components in the MA corrupted PPG signals by estimating the spectra of the same. In SVD method noise reference signal generated using the singular values of decomposed PPG signals.

ICA represents the mixed signals in motion corrupted PPG signal as statistically independent components. In an early method Time Varying Step size Least Mean Square (TVS-LMS) filter, filter coefficients are updated using a decaying factor. Due to the non-stationary nature of PPG signals this algorithm can be further improved by updating the step size parameter also. This adaptive step size updating is done using gradient vector, i.e., derivative of the weight vector at a sample and a small positive constant that controls the updation of step size parameter.

C. Hilbert Huang Transform (HTT)

This method uses Empirical Mode Decomposition (EMD) to decompose a signal and Hilbert transform for spectral analysis. EMD is the fundamental step in HTT. EMD decomposes a signal into finite and small number of components. These components are called Intrinsic Mode Function (IMS) and they form a complete signal and are nearly orthogonal. The requirement for a function to be an IMF can be seen at [7]. The procedure of extracting IMFs is called sifting. Sifting process first identifies all local extrema in the data. Then connects all local maxima and minima to produce upper and lower envelopes respectively. For this cubic spline interpolation is used. Instantaneous frequency of each IMF as a function of time can be obtained using Hilbert spectral analysis.

The localized features of the signal can be finally obtained from Hilbert spectrum which is frequency- time distribution of signal amplitude. Sun et al. [8] proposed an algorithm for clinical applications using EMD and Hilbert transform. In that method a median filter used for base line wandering removal and to get a detrended PPG signal. IMFs are extracted from the detrended PPG signals by EMD.

The energy level of each IMF calculated using Hilbert transform which is then utilized for discarding motion artifacts. However performance of EMD is limited in case of narrow band signals. Other problems with HTT are end effects of EMD, spline problems, mode mixing problem. Method in [8] suffers from mode mixing problem. It can be avoided using EEMD.

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EEMD: In EEMD, white noise is added to data set and noise added data set is decomposed into IMFs. The process is repeated with different noise series. Finally mean of each IMFs are taken.

D. Independent component analysis(ICA)

A multivariate signal can be decomposed into additive components using independent component analysis. Requirement for decomposition is that the additive components should be statistically independent non-Gaussian signals. It is a method used for blind source separation. As the PPG signals and MA are independent ICA can be used to separate PPG signal. Let the observed mixed signal be ‘Y’ and independent sources be ‘S’ then the relationship among them can be represented as:

$$Y= MS \qquad (1)$$

where M is an unknown mixing matrix. The different independent sources can be found from the model. If a specific independent component is to be extracted the problem reduces to constrained Independent Component Analysis (cICA). Peng et al.[9] proposed cICA with adaptive filtering to remove the motion artifacts in the PPG signal. Algorithm models the motion corrupted PPG signal as a linear mixture of MA and cleansed PPG. Unlike ICA algorithm, cICA algorithm is not concerned with the number of independent sources and extracts a particular source. cICA algorithm uses the periodic behaviour of the PPG signal for extracting that signal. However when the hand movement is also periodic this algorithm degrades.

E. Fixed interval Kalman smoother

Kalman filtering is a widely applied technique in time series analysis. Filtering algorithm works in two step process. In the prediction step the Kalman filter produces estimates of the current state variables along with their uncertainties. Once the outcome of next measurement is observed the estimates are updated using a weighted average with more weight being given to the estimates with higher certainty. The algorithm is recursive. It can run in real time using only the present input measurements, previously calculated stateand its uncertainty matrix. No additional past information is required.

The optimal fixed interval smoother provides the optimal estimates using measurements from a fixed interval. This is also called Kalman smoothing. There are several smoothing algorithms in common use such as Rauch-Tung-Stribel (RTS) smoother, modified Bryson- Frazier smoother, minimum variance smoother etc. Lee et al. [10] proposed an algorithm which uses the method of Kalman smoother. In that state estimate at particular time point inside a fixed time interval is estimated using a fixed interval smoother. Algorithm used the RTS smoother accuracy of this type of smoother is superior to that of other filters such as Normalised Least Mean Square (NLMS) or Recursive Least Square (RLS) filters. However this can only be used in non-real time applications and requires a large amount of memory. Also it’s a computationally highly complex algorithm.

F. Singular spectrum analysis (SSA)

SSA is a tool for time series structure recognition and identification. SSA is a signal decomposition technology in which the signal matrix is decomposed into a number of singular matrices which are additive components. These additive components may be trend components, oscillatory components and noise components. These components are analysed to recognize and remove the unwanted noisy or interference components. SSA is performed in four steps of embedding, SVD, grouping and reconstruction. In the embedding step one dimensionaltime series is represented as a sequence of vectors. Resulting matrix is called trajectory matrix. This trajectory matrix is then decomposed into bi-orthogonal rank one matrices using SVD.

These two steps constitute the decomposition stage of SSA. The next two steps of grouping and reconstruction constitutes the reconstruction stage of SSA. In the grouping sub-step bi-orthogonal rank one singular matrices are grouped into distinct groups and the matrices in a particular group is added. The resulting structure gives the representation of trajectory matrix as a sum of different matrices called resultant matrices. In the reconstruction sub-step each resultant matrix is converted to a time series. This time series is an additive component of the original time series.

Thus several additive time series of the original time series is obtained and the operation is called diagonal averaging. Zhang et al. [12] proposed a robust HR monitoring algorithm from motion corrupted PPG signals in the name TROIKA. Algorithm uses SSA for signal decomposition and reconstruction.Boloursazmashhadietal. [13] also uses SSA but with an additional adaptive filtering stage. Zhang et al applies SSA on PPG signals while Boloursazmashhadietal. on simultaneously recorded acceleration signals to generate noise reference signal for adaptive noise filtering.

G. Multiple Measurement Vector (MMV) model

Many of the recent HR monitoring algorithms from motion corrupted PPG signals uses simultaneous acceleration data to remove motion artifacts. But most of the methods estimates the spectra of motion corrupted PPG signals and acceleration signals separately and in most cases using different spectrum estimation methods. After spectrum estimation the spectral peaks of MA in raw

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PPG spectrum is identified checking spectral peaks in MA at corresponding frequency bins. Since the two estimates are computed using different methods and separately, spectral peak in MA may not occur at the same location in PPG spectra but at a different location even if it was caused by same hand movement. As a result MA peak in the raw PPG signal may go un-observed. Also in some cases MA spectra may have a dominant peak within the frequency bin where the previous HR peak locates. So the algorithm keeps that peak by misinterpreting it as HR peak. So in order to avoid these problems MMV method can be used to jointly estimate the spectrum of raw PPG and acceleration signals. The MMV model can be expressed as:

$$Y = \Phi X + V \qquad (2)$$

where Y is $M \times L$ matrix with measurement vectors as columns. Φ is $M \times N$ redundant DFT basis. V is $M \times L$ noise vector and X is $N \times L$ desired solution matrix. The matrix X is row wise sparse i.e. only a few rows in X are non-zero while most rows are zero or nearly zero. It is referred to as common sparsity constraint. MMV model exploits the common structure in the two signals and it has better reconstruction performance for a given sparsity level and compression ratio.

Here the measurement vectors are PPG signal and acceleration signals. The spectral peaks of MA in the raw PPG spectra can be easily found by checking spectral peaks in acceleration signal spectra at corresponding frequency bins with the help of this common sparsity constraint. This method does not require signal decomposition and temporal difference operation as in [12]. Spectral analysis steps also simplified. Zhang et al. [14] proposed joint sparse spectrum reconstruction method which is accomplished using MMV model. This algorithm eliminates some of the drawbacks in [12].

H. Closest Subspace Subtraction

HR monitoring from PPG signals during intensive physical exercise can exploit the fact that MA and HR signal components can be distinguished by different subspaces and it can be used for effective MA removal. Baca et al. [15] proposed an algorithm named Closest subspace Algorithm for Reducing Motion Artifacts (CARMA). The algorithm consists of two steps. Motion Artifact Removal (MAR) and Adaptive Tracking (AT).

MAR step decomposes the acceleration signal and PPG signal using SVD. SVD of acceleration signals gives subspace of motion signals (SMS). A closest subspace to this subspace of motion signal is subtracted from the decomposed PPG signal to get the subspace of HR. FFT algorithm is used to find the dominant peaks in the spectrum of singular value decomposed signals. Corresponding frequencies are used in MA removal. The MA removed HR sequence is then smoothed. The main advantage of this algorithm is that it does not lose the track of true HR. so that the requirement initial resting phase can be avoided.

I. Cepstrum Technique

Inverse transform of the logarithm of the estimated spectrum of a signal is called cepstrum of that signal. The cepstrum can be seen as information about rate of change in the different spectrum bands. The harmonic nature of HR is exploited in the cepstrum technique. Chuang et al. [16] proposed an algorithm for removing motion artifacts using cepstrum technique. Algorithm consists of three main steps. Cepstrum estimation is the first step. In the next step periodic components in the cepstrum is enhanced. In the last step a time domain signal is reconstructed by inverting complex cepstrum.

IV. SPECTRAL ANALYSIS

Estimation of heart rate in time domain is difficult when the effect of MA is strong. A possible way to circumvent this problem is to transform the signal from time domain to frequency domain after de-noising the signal. Some of the proposed algorithm uses a spectral analysis stage for estimating HR after MA removal [12]-[14]. Power spectrum estimation can be used for spectrum estimation. Periodogram algorithm computed using fast Fourier transform (FFT) is such a widely used power spectrum estimation algorithm. But periodogram estimator is an inconsistent spectrum estimation algorithm and it has serious leakage effect. Also, it suffers from high variance. So instead of this non parametric spectrum estimation methods high resolution line spectrum estimation methods can be used.

But high resolution spectrum estimation algorithms such as MUSIC require model order selection which is difficult for MA contaminated PPG signals. Because the spectra of MA are complicated and time varying. So sparse signal reconstruction (SSR) methods are used for high resolution spectrum estimation [12],[17]-[21]. SSR based spectrum estimation techniques offers high spectrum resolution, low estimation variance and increased robustness compared to non-parametric spectrum estimation methods such as periodogram.

And compared to conventional line spectral estimation methods the SSR based spectrum estimation has improved estimation performance and doesn’t require model order selection. However SSR requires that the spectrum to be estimated is sparse or compressive. Sparse or compressive spectrum is that most of the coefficients are zero or nearly zero while only some coefficients have large non zero value.

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The method of SSR is applied in Zhanget al [12]. But applying SSR only to the MA contaminated PPG signals while estimating the spectra of acceleration signals using periodogram algorithm causes wrong selection of peak MA components as described in the section III. I. This problem can be eliminated by using joint sparse spectrum estimation [14].

Generally the spectral analysis stage of many algorithms proposed consists of three sub-steps. These sub-steps play an important role in estimating the HR. Initialization, peak selection and peak verification steps are described in coming subsections. Initialization and peak selection constitutes the spectral peak tracking step which is followed by peak verification. Zhang et al. [12], [14] used peak tracking and verification steps.

A. Spectral peak tracking

Peak tracking exploits the harmonic relation of HR and the observation that HR values in two successive time windows are very close if the two time windows overlap largely. Initialization: Wearers have to reduce motions in this stage. HR is estimated by choosing the highest spectral peak in PPG spectrum during this stage. The estimated HR in this stage is used in successive time windows for estimating the HR in that time window. This will help not to lose the track of HR. Peak Selection: Different peak selection algorithms are used in [12] and [14]. In TROIKA framework [12], two search ranges are set by using the initial HR estimate. First search range is for fundamental frequency and second search range is for harmonic frequency.

Then three peaks in each search window are selected. In that set if there exist a peak pair with harmonic relation then the peak in the first search range is selected and corresponding frequency location index is selected as HR. if there is no peak pair, then optimization is required for HR estimation. If no peaks at all, previous frequency location index of HR is selected as current HR.

In JOSS frame work [14], first a search range is set using the value of previously estimated heart rate. Then three highest peaks in that search range is found. If there are no peaks in that search range then the range of search range is increased and again three highest peaks are found. Even after this if there is no peaks choose the previously selected HR as current HR.

B. Peak Verification

The peak selection method sometimes wrongly tracks the spectral peaks. Thus a verification stage is necessary. Some rules are assigned for this verification. The first rule is that the change of BPM (Beat Per Minute) values in two successive time windows is limited to 10 BPM. Once the change exceeds 10 BPM, a regularization parameter is provided. The second rule is to prevent lose of tracking over a long time. In JOSS framework if the BPM value in two successive time window exceeds 12 BPM, previous value is chosen as current value.It also uses a discovery mechanism for preventing lose of tracking of HR.

V. CONCLUSION

HR monitoring and controlling is very important in fitness applications. Thus the design of wearable devices that can efficiently monitor HR gained much attention in recent years. The main problem faced in HR monitoring is the presence of motion artifacts in the acquired PPG signal. Many signal processing algorithms are proposed to remove the effect of motion artifacts to date. In this paper different MA removal algorithms proposed from the early stages of this technology are re-evaluated. Challenges in HR monitoring in an intensive movement scenario are included. Various signal processing methods are explained in detail.

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BIOGRAPHY

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