Heart Rate Monitoring During Intense Physical Activities Using A Motion Artifact Corrupted Signal Reconstruction Algorithm in Wearable Electrocardiogram Sensor

S. M. A. Salehizadeh
Biomedical Engineering Department
University of Connecticut
Storrs, United States

Y. Noh
Biomedical Engineering Department
University of Connecticut
Storrs, United States

K. H. Chon, *Senior Member, IEEE*
Biomedical Engineering Department
University of Connecticut
Storrs, United States

***Abstract*— Accurate estimation of heart rates from electrocardiogram (ECG) signals during intense physical activity is a very challenging problem. In this study we investigated a novel technique to accurately reconstruct motion-corrupted ECG signals and HR based on time-varying spectral analysis. The algorithm is called Spectral filter algorithm for electrocardiogram Motion Artifacts and heart rate reconstruction (SegMA). The idea is to calculate time-frequency spectrum of ECG for each time shift of a windowed data segment and use the information from the spectrum to reconstruct HR during movement. The SegMA approach was applied to a datasets recorded in Chon Lab that includes 17 min recordings from 4 subjects during a challenging experimental protocol including walking, jogging, running, arm movement, wrist movement, body shaking, and weight lifting activities. The ECG and tri-axial accelerometer data were recorded from a wrist bands on both right and left wrists that are connected with wire through a tight suit. The reference ECG signals were recorded from chest using Holter monitor. The algorithm's accuracy was calculated by computing the mean absolute error between SegMA reconstructed HR from the wrist ECG and the reference HR from the Holter ECG. The average estimation errors using our method on this datasets are around 1 beats/min. These results show that the SegMA method has a potential for ECG-based HR monitoring in wearable devices for fitness tracking and health monitoring during intense physical activities.**

Keywords*— *Electrocardiography; Motion Artifact; Heart Rate Monitoring; Physical Activities; Signal Processing

I. Introduction

Cardiovascular disease is the leading cause of death in the world. Considering the fact that a majority of such deaths due to cardiac arrest occur before the patient can get the needed medical care, the patient should be continuously monitored for real time detection of the events that can portend cardiac arrest [1-3]. The electrocardiogram (ECG) is the main measurement device for effectively diagnosing cardiovascular health, other cardio-respiratory related diseases and can be used as a guide for cardio-fitness therapy.

Wearable health monitoring systems (WHMS) enable continuous, reliable and long-term monitoring of vital signs and physiological signals during daily normal activities [27]. Recently a variety of WHMS have also been introduced in an attempt to reduce size, improve comfort and accuracy, and extend the duration of monitoring. Product concepts and prototypes of ECG patches have been introduced by several companies and research groups such as: Curvus, Corventis, iRhythm, Toumaz and Delta [4-6]. The effectiveness of WHMS can be significantly impaired by motion artifacts which contaminate the signal and that can lead to errors in estimation of cardiac parameters and trigger false alarms. For Holter systems, motion artifacts often lead to difficult interpretation of whether or not certain arrhythmia has truly occurred even when three or five different channels of ECG data are considered.

Reducing the motion artifact would extend the applicability of ambulatory monitors to situation of greater activity as encountered in most daily-life situations. Noise and motion artifacts are caused by several factors, such as baseline wander (BW), power-line interference (PLI), electromyography (EMG) noise and skin-electrode motion artifacts (MA) [7, 8]. In practice MAs are difficult to remove because they do not have a predefined narrow frequency band and their spectrum often overlaps that of the ECG signal [9]. The corruption introduced by motion artifacts is random variables which depend on the electrode properties, electrolyte properties, skin impedance, and the movement of the patient. Consequently, development of algorithms capable of reconstructing the corrupted signal and removing artifacts is challenging.

Numerous methods for motion artifact detection and reduction have been proposed in literature [11-25]. Traditional de-noising techniques are based on time averaging [10] and frequency analysis such as filter banks [10] or wavelet transforms [11]. In adaptive filtering, a filter is applied after adjusting its parameters to a time varying noise. This is particularly useful when the noise is non-stationary, like in the case of ambulatory motion artifacts. However, a reference signal has to be additionally recorded together with the ECG. As sources of ECG and motion artifacts are uncorrelated, blind source separation (BSS) techniques could be used for separating both signals [20-22]. A combination of PCA and ICA was also proposed by Chawla [24] for ECG de-noising.

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Lee et al. used empirical mode decomposition (EMD) approach to detection of Motion and noise artifact for the purpose of detection of atrial fibrillation from ECG recordings [25]. The main issue with BSS algorithms is its heavy computational cost and that they are not suitable for real-time processing purposes.

In this paper, an approach for HR signal reconstruction is presented using time-varying spectral analysis. The algorithm is called SegMA and is comprised of four distinct stages: (1) Taking derivative of downsampled ECG (2) time-varying power spectral density (PSD) calculation, (3) spectral filtering, (4) HR reconstruction. We will show that SegMA can improve HR estimations by almost 12 time better accuracy than without SegMA reconstruction.

The remaining of this paper is organized as follows: Section II presents the experiments and the ECG wearable used in this study. SegMA algorithm procedure and the details of four steps are explained in section III. The results of SegMA algorithm on the dataset from 4 subjects is included in section IV. Finally we conclude the paper in section V.

II. Experimental Setting

An experiment with a physically challenging protocol that includes 17-min ECG recordings from 4 healthy subjects was designed, in which each subject was asked to wear a wrist-worn ECG device as shown in Fig.1. The wearable system is called NohChon and was custom designed in our laboratory. It consists of two wrist modules which are designed to fabricate a 1-channel ECG signal (Lead I configuration) on the top of right and left wrists. This device was designed and developed for ECG measurement based on two leads with virtual right-leg driven circuit and provides a frequency band at -3 dB from 0.05 to 150 Hz with second-order high-pass and low-pass filters to cover the full ECG range. In both modules, 3-axis accelerometric data were collected to reject MNAs using accelerometer (MMA8652FC, Freescale, TX, USA) which has a sensitivity of ±2 g. A wire was connected between both left and right wrist-based electrodes to produce an ECG signal and is threaded to a compression shirt for minimizing motion artifact than can be caused by wire movements. ECG signal was sampled at 360 Hz with 12-bit resolution over a range between 0 and 3.3 volts. Electrodes for ECG measurement are carbon black (CB) based film electrode [30].

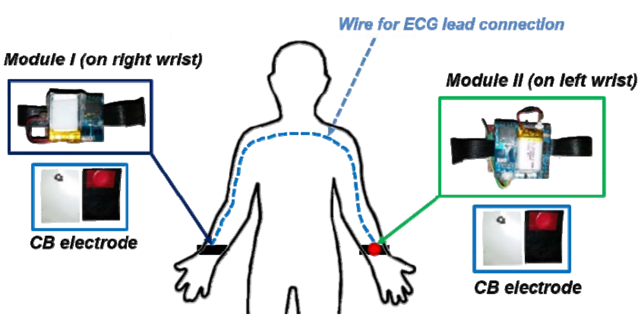


Fig. 1. "NohChon" Wrist ECG Wearable Device

Each subject was asked to perform different types of physical activities (Walking/Running, Arm Movement, Wrist Rotation/Shaking, Weight Lifting/Box Movement) during the experiment to investigate the performance of the algorithm in variety types of daily activities and movements. The reference ECG signals for evaluation of SegMA were recorded from a chest using Holter monitor.

III. Methodology

The procedure for our HR monitoring algorithm during intensive movements is presented in the following subsections

A. *ECG Preprocessing*

The first step in SegMA algorithm is to resample ECG to ¼ of its original sampling rate. This improves the frequency resolution in the time-frequency spectrum. Next a derivative of the resampled ECG signal is computed so that the R-peaks are accentuated. The idea is by derivative of signal, motion and noise artifacts can be reduced to some extent as long as motion is not abrupt and the samples are uniformly corrupted by motion. Fig. 1 represents representative ECG recordings from both NohChon wrist device and a Holter. This figure shows the HR estimations from R-R interval of the reference and a wrist ECG. The reference HR provides a clean and accurate HR and the estimated HR from wrist ECG signifies inaccurate HR estimation especially during running, wrist movements and weight lifting periods of experiment. This figure indicates the necessity of using a HR reconstruction approach.

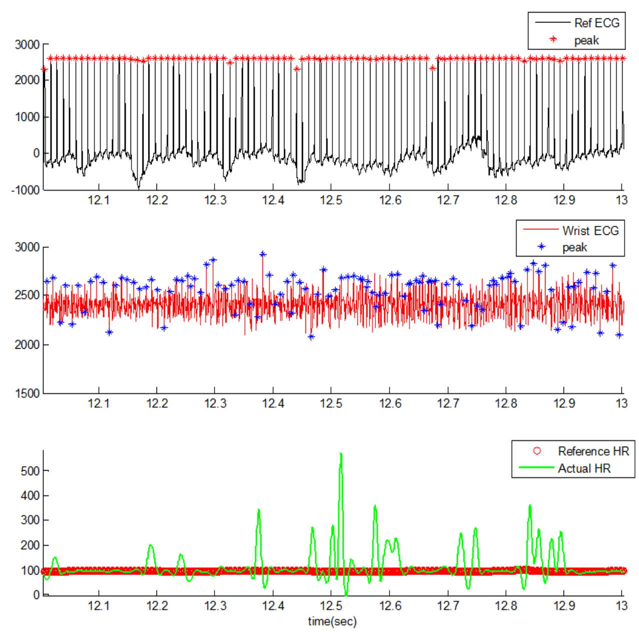


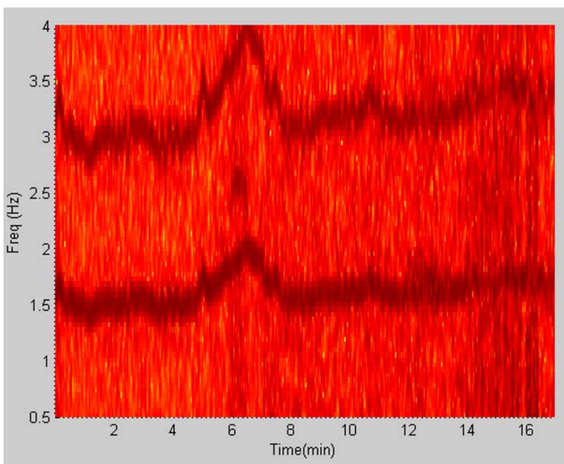
Fig. 2. A segment of ECG recordings and estimated HR from subject #3 during wrist rotation movement activity. [top]: reference ECG, [middle]: Wrist ECG and [bottom] reference HR vs actual HR

B. *Time-Varying Spectral Analysis of ECG data*

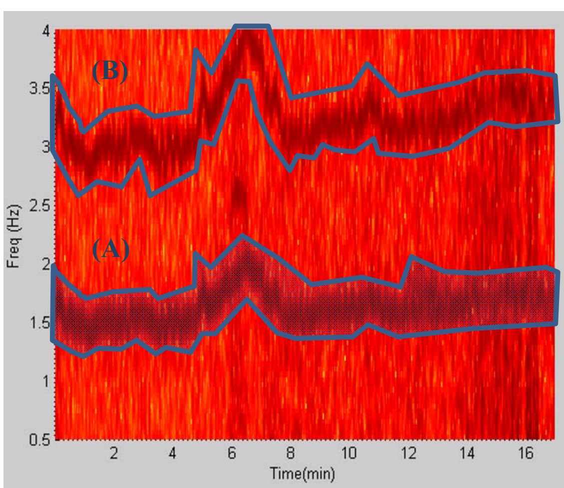
We produce a time-varying spectrum by taking a T-sec window of the signal and computing the power spectral density

(PSD) [26] of the segment and then sliding the window through the whole dataset which yields a time-frequency matrix in which each array represents the power of the signal corresponding to a specific frequency and sliding time-step (shift) of S-sec. The window segment length T was set to 8 seconds and was shifted (S) by 2 seconds. The assumption of 8 second data length largely stems from the fact that heart rates do not change instantaneously; hence, 8 second duration is a reasonable choice.

As a representative example, the resultant frequency components in the time-frequency matrix of recordings from subject #3 of the dataset, for a window length of 8 seconds that is shifted by every 2 seconds, is shown in Fig.3a. From the Fig.3b, time-frequency plot of the ECG signal, it is observed that there are two major frequency components (A) and (B) in the time-frequency spectrum plot: one of them appears to represent HR and the other may represent the first harmonic of HR. In order to verify this conjecture we need to extract these components from time-frequency spectrum.



(a)



(b)

Fig. 3. Time-Frequency spectra of recording #3: (a) ECG signal time-frequency spectra, (b) Blue areas and letters represent HR trace and its harmonic in the ECG spectra.

To this end, in the next phase of SegMA algorithm, we apply a filtering strategy to keep the major components of spectrum and remove the unnecessary information.

C. Spectral Filtering

Assuming that the HR frequency component is the dominant peak in the power spectral density (PSD) of each 8 sec window of a clean ECG signal, the filtered time-frequency spectrum using the first two largest peaks of PSD at each window can be extracted as shown in Fig. 4. After obtaining the power spectral density at each window, HR frequency is assumed to be confined in the range [0.5 Hz – 3 Hz]. In general, HR frequency in the power spectral density of ECG at each window can have three different scenarios: (1) ECG is devoid of MA and there is no spatial gap between the electrode and the subject's skin during recording, (2) ECG is corrupted by MA and there is no spatial gap between the electrode and the subject's skin during recording and (3) There is a spatial gap between the electrode and the subject's skin during recording. For the ideal case (1), HR can be extracted and it is most likely represented as the highest peak in the ECG spectrum. For case (2), MA dynamics can result in the dominant peak and HR frequency peak's magnitude become smaller than the MA frequency peak in the power spectrum. The only scenario that makes it difficult to extract HR from the spectrum is scenario (3) when there is a spatial gap between the ECG electrodes and the subject's skin during recording. In this scenario, assuming that the motion artifacts are short lasting, the missing HR values can be interpolated using the cubic spline technique.

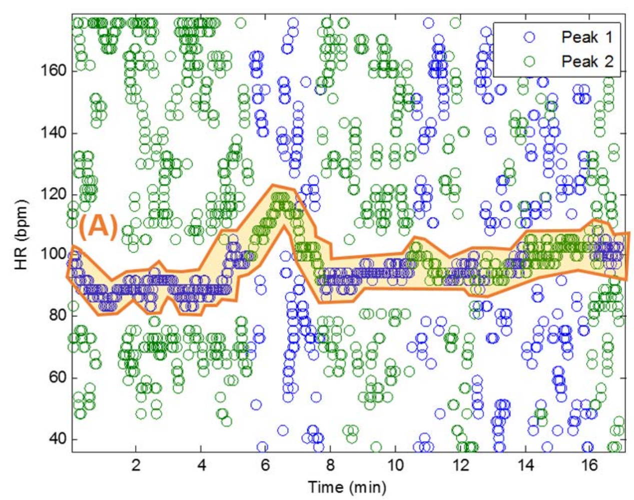


Fig. 4. Spectral Filtering. ECG time-frequency spectrum: Blue, Green circles correspond to the first two highest peaks in the defined HR frequency range of (30-180 bpm), respectively, at each sliding window. (b) Tracking of HR trace in the filtered ECG spectrum.

D. Heart Rate Tracking & Extraction

The next step is to extract HR frequencies with time from Fig. 4. Note that in Fig. 4, there are two peaks at each time instance, thus, the question is how to identify which of the two peaks represents the HR at each time point. For the initial time window of 8 seconds, we require a clean data segment so that true HR can be determined. This scenario is case 1 described above in the spectral filtering section, and the detection of HR is simply the highest peak in the spectrum. The next step is to estimate HR for each sliding window of data. At this step of the algorithm, the goal is to choose a HR peak in the ECG spectrum with the knowledge of estimated HR values in previous time windows. In this step there are two main scenarios: (1) no peak exists in the spectrum that can represent HR, and (2) there is a spectral peak among the first two highest peaks of spectrum that belongs to the HR component. In case (1), where HR is not detectable in the window (e.g. due to spatial gap between the ECG electrode and skin), in real-time implementation the algorithm takes the previous window's HR value as the current HR (or simply uses the moving average of several past HR beats or some other variant), however in offline processing, a cubic spline interpolation can be used to fill in the missing HR information. In the more general case (2), where the HR peak is among the first two highest peaks in the spectrum, two possible scenarios can occur: (2-A) the windowed ECG signal is clean and the first highest peak in the spectrum represents the HR fundamental frequency, (2-B) the windowed ECG signal is corrupted by movement and the second peak corresponds to HR, (2-C) while the HR spectral peak is detectable, the difference between its value and that of the previous HR is more than 15 bpm, so it will be replaced by the most recent HR value from a previous window segment (or a moving average of several past HR beats or some other variant). We set a criterion that the HR value cannot change more than 15 BPM from a previous time window. It can be observed from Fig.5 that in most cases, the blue circle which represents the largest spectral peak is chosen but in other cases, green circles are chosen for certain time points. For the HR peaks associated with the green, they are chosen because either the first highest peak is related to MA or the highest magnitude peak deviates more than 15 BPM from the previous HR value.

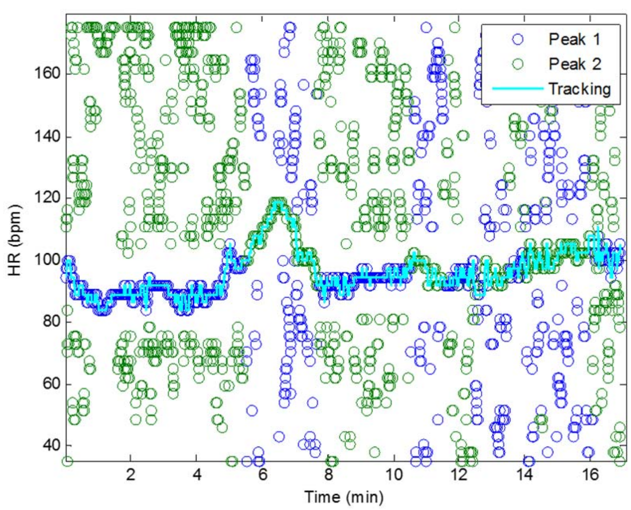


Fig. 5. HR Tracking and Extraction. Tracking of HR trace in the filtered ECG spectrum.

Fig.6 shows the SegMA reconstructed HR (red color) from ECG spectra of recording#3 using our proposed approach along with the 8-sec moving average of reference ECG-derived HR (black color). In order to calculate the performance of the SegMA algorithm, the error value in each time window was calculated from the estimated HR to the reference ECG-derived HR.

Two measurement indices of absolute error similar to the indices in [18] were used.

$$Error(1) = \frac{1}{W}\sum_{k=1}^{W}\left|HR_{SegMA}(k) - HR_{ref}(k)\right| \quad (1)$$

$$Error(2) = \frac{1}{W}\sum_{k=1}^{W}\frac{\left|HR_{SegMA}(k) - HR_{ref}(k)\right|}{HR_{ref}(k)} \times 100\% \quad (2)$$

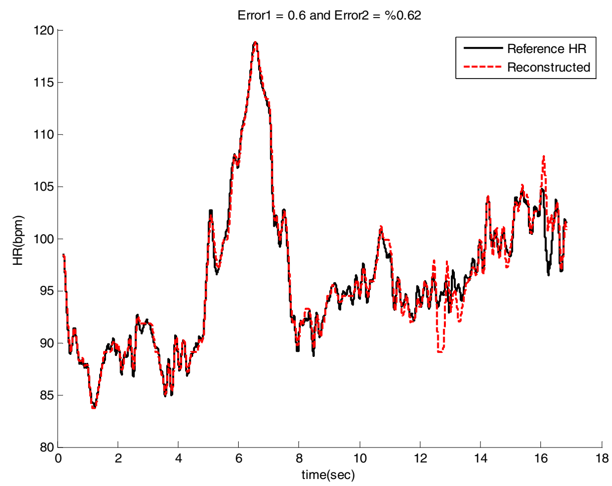


Fig. 6. Comparison of reconstructed HR obtained from SegMA to reference HR estimated from simultaneous ECG recordings#3.

IV. Results

Table (I) represents the average absolute error (E1) and the average absolute error percentage (E2) of HR estimations of the proposed SegMA algorithm on the dataset. Our SegMA algorithm is compared to the HR estimations before applying the reconstruction algorithm, where both before and after reconstruction estimations are compared to the reference HR from ECG, and reference SpO2 from Masimo commercial device. Table (II) shows that SegMA on average improves the HR estimations with around 1200% comparing to those estimations before reconstruction. Improvement rate was calculated as follow

$$\operatorname{Im}Rate1(\%) = \frac{1}{W}\sum_{k=1}^{W}\frac{\left|Error1_{SegMA}(k) - Error1_{Act}(k)\right|}{Error1_{SegMA}(k)} \times 100\% \quad (3)$$

$$\operatorname{Im}Rate2(\%) = \frac{1}{W}\sum_{k=1}^{W}\frac{\left|Error2_{SegMA}(k) - Error2_{Act}(k)\right|}{Error2_{SegMA}(k)} \times 100\% \quad (4)$$

TABLE I. SEGMA ALGORITHM PERFORMANCE COMPARISON

Subject	Actual HR estimation error		SegMA HR estimation error	
	E1	*E2%*	*E1*	*E2%*
1	13.66	13.98	**1.31**	**1.46**
2	22.69	24.37	**2.05**	**2.16**
3	8.66	8.71	**0.60**	**0.62**
4	15.32	15.06	**0.76**	**0.81**
mean ± std	18.08 ± 5.8	15.53 ± 6.5	**1.18 ± 0.7**	**1.26 ± 0.7**

TABLE II. IMPROVEMENT RATE PERCENTAGE AFTER RECONSTRUCTION USING SEGMA ALGORITHM

Subject	SegMA Improvement Rate	
	ImRate1%	*ImRate2%*
1	943.1	857.5
2	1006.9	1028.2
3	1343.3	1304.8
4	1915.8	1759.3
mean ± std	1302 ± 445.1	1237 ± 393.7

The results for recording #4 are shown in Fig. 7. It can be seen that the E1 for this subject is around 0.76 bpm.

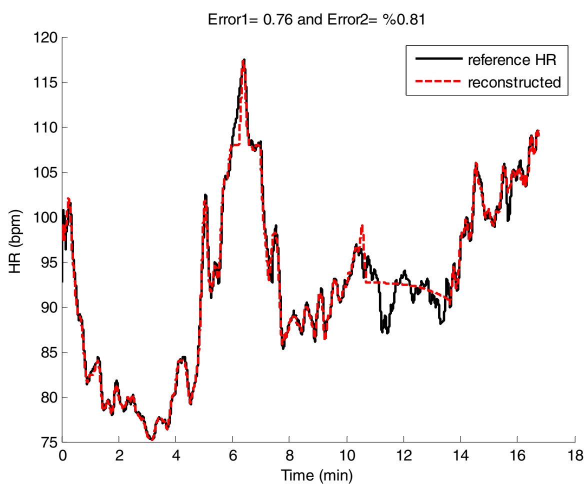


Fig. 7. Subject 4. Reconstructed HR vs. reference HR (estimated from reference ECG)

A video of the real-time implementation of SegMA algorithm is available from [28].

V. CONCLUSION

Wearable sensors have recently enjoyed much public attention and interests. More importantly, these devices provide an attractive feature where for the first time individuals can track and manage their own health-related data. In spirit of this recent development in wrist-worn sensors, the objective of our work was to develop a robust and accurate algorithm that can mitigate motion artifact so that more accurate heart rates can be estimated from electrocardiogram (ECG) signal. Certainly, this is challenging since wrist-worn devices are especially prone to more varied motion artifacts when compared to sensors placed on other parts of the body.

While wearable ECG devices are normally worn as a Holter monitor or a patch on the chest, recent advances in non-contact capacitive and dry electrodes has resulted in textile worn ECG measurements. The form factor and locations of these textile-based ECG sensors can be found from the traditional ECG electrode placements around the chest area to electrodes incorporated directly into a belt [29, 30]. So we developed a wrist-worn ECG device using our own dry flexible electrodes [29, 30], and this is the device that was used to collect experimental data as detailed in the section II.

Our algorithm, SegMA, based on time-varying spectral analysis of the ECG signal is introduced to combat motion artifacts. To fully test the robustness of the SegMA algorithm, the design of the type of motion artifacts introduced for our experiment was cognizant of the wide variety movements subjects might encounter during their daily activities. In all of the recordings, the reference HR was calculated from an ECG signal that was collected simultaneously with the ECG signal. The estimated HR was calculated from the spectrum of ECG in 8 second time windows. It was shown that the proposed SegMA algorithm can be used for tracking fast HR changes as they varied more than 70 beats/min in less than 2 minutes and despite severe motion artifacts since the subjects were running at a full speed on a treadmill, the average error of around 1.20 bpm was found when compared to that of the reference ECG. This average error also includes when subjects were introducing challenging motion artifacts by performing wrist shaking and bending exercises.

The results from Table I show that the SegMA algorithm can be effectively applied to monitor HR from ECG wrist wearable devices. We made several observations while analyzing the data. The tracking ability of the SegMA algorithm decreased as the dynamics of the motion artifact increased. This phenomenon mostly was observed while dealing with abrupt movements which consequently made it more difficult to track the HR-related frequencies in the spectrum.

The main sources of noise and corruption during recording ECG signal using NohChon wrist band was (1) movement of wire inside of tight suit, (2) electromyogram (EMG) interference when subjects were either shaking or bending the wrist, and (3) contact issues with the skin-electrode interface during movements. We showed that SegMA is able to address the first two type of noise and motion artifacts. However the third noise type which can be due to gaps or poor contact between skin-electrode interfaces is the most challenging scenario for any motion artifact reconstruction algorithm. This is because a gap between electrode and skin, ECG signal strength would decrease due to impedance mismatch [34], and if severe, it can lead to loss of signal.

The proposed SegMA algorithm can be implemented in real time. We have found that the algorithm written in Matlab takes around 75 msec on data segmented into 8 seconds. Therefore, given the high accuracy of the proposed approach in estimating HR despite severe motion artifacts, this method has the potential to be applicable for real-time implementation on wearable devices such as smart watches and ECG-based fitness sensors.

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