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Motion Artifact Detection and Reduction in Bed-Based Ballistocardiogram

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ABSTRACT Non-intrusive sleep monitoring is critical for certain populations such as severely disabled autistic children. Nocturnal disturbance analysis is an important diagnostic tool for assessing sleep issues. The objective of this paper is to detect and minimize the effects of motion artifacts in signals recorded via an unobtrusive electromechanical film-based ballistocardiogram (BCG) sensor integrated into a smart bed system. The goal is to have a reliable estimation of beat-to-beat (B-B) interval. The proposed algorithm includes two main stages: a motion detection algorithm followed by a motion artifact removal system. Motion detection involves a sequential detection algorithm in which successive data frames are compared to two thresholds: upper and lower thresholds. Each motion corrupted frame can then be reconstructed by an approach that relies on a parametric model of the BCG signal. Exploiting the fact that the underlying BCG parameters (J-peak-to-J-peak interval, J-peak-to-K-peak amplitude, and the most significant frequency component) change slowly and are correlated across time; an autoregressive model-based tracking and Wiener smoother based parameter estimation strategies are proposed. The experimental results are presented to demonstrate the effectiveness of the proposed motion artifact detection and removal algorithms. The probability of detection of 96% and high average coverage of 84% with over 90% precision for the estimated B-B intervals are achieved on recordings for 19 h of sleep from three subjects. Our novel motion detection and removal methods demonstrate the feasibility of using bed-based BCG signals for providing a reliable unobtrusive way to estimate the B-B interval in the presence of motion.

INDEX TERMS Autism, autoregressive model, ballistocardiogram, motion artifact detection and removal, Wiener smoothing.

I. INTRODUCTION

It is a well-known fact that our ability to function is dependent on the quality of our sleep. However, most of the studies that have uncovered this understanding have been performed on neurotypical individuals. For those with severe disorders such as Asperger's disorder or individuals who are severely autistic, this link is not as well defined. Recent studies have started to show that children with autism tend to suffer from sleep problems more than neurotypical children [1], [2] with 50% to 80% of autistic children having some type of sleep problem. The gold standard for assessing sleep quality is polysomnography (PSG). The PSG involves a multitude of sensors, electrodes, and associated cabling (e.g., belts put around the chest to measure breathing). Such a system is uncomfortable, intrusive, and intolerable for severely disabled autistic children. Also, for electrocardiogram (ECG), electro-oculograms (EOG), and electroencephalography (EEG) as part of PSG, the on-body electrodes are not suitable for continuous long term sleep monitoring. One less intrusive option is actigraphy [3] which uses accelerometer data to classify sleep and wake periods based on body motion. However, most actigraphy systems are implemented with wearable devices. Even though actigraphy offers a less intrusive means to assess sleep quality, it does not consider any physiological parameters, and wearable actigraphy sensors are not an ideal solution for use with severely disabled autistic children. Approaches for estimating sleep quality based on a subset of the physical

(i.e. activity) and physiological (i.e. heart rate variability, respiratory rate) parameters measured by the PSG are an area of active investigation [4], [5].

A promising, unobtrusive methodology that monitors cardiac activity is ballistocardiography. Every time the heartbeats, the body recoils in response to the heart's micromovements. A recording of the whole-body's recoil response is known as the ballistocardiogram (BCG). In contrast to the gold-standard for heart rate measurement, electrocardiography, which requires electrical contact between the body, BCG signals can be recorded unobtrusively with sensors hidden within a bed system with no electrodes needed to be worn by the subject. Different kinds of sensors have been considered in a bed-based BCG acquisition system [6], [7]. The clean signal measured by sensors can be used to extract heart rate from the BCG along with respiration rate. However, the reliability of the BCG signal is often unsatisfactory for long-term recordings due to its high sensitivity and susceptibility to motion artifacts. These motion artifacts can cause significant challenges in heartbeat estimation. In this study, we present a method for motion artifact detection and mitigation in bed-based BCG signals. Unlike previous methods, we propose a novel algorithm to detect and eliminate the motion artifacts in BCG signals so that we are able to extract useful sleep features unobtrusively. Our long-term goal is to develop an unobtrusive modality for assessing sleep quality of autistic children; we plan to use the BCG signal for analyzing cardio-respiratory parameters and inferring sleep quality from these parameters and further relate them to their daytime behaviors.

A. RELATED WORK

Since one of the major problem in all sensing modalities are motion artifacts, motion artifact detection and removal has received significant interest. For example, in ECG signals there has been a large number of proposed approaches for artifact detection and mitigation. These include linear filtering [8], adaptive filtering [9], wavelet denoising [10], and Bayesian filtering methods [11] for motion artifact detection and adaptive filtering [12], [13], wavelet-based [10], [14], [15] for removing motion artifact. A motion detection method has been proposed in [16] using energy of load cells located in four corners of the bed. Krishnan *et al.* [17] proposed a two-stage approach for photoplethysmogram (PPG) data based on higher order statistical parameters. Neyman-Pearson detection rule was chosen as detection unit and a frequency domain independent component analysis (FD-ICA) technique along with period estimation as motion reduction. Motion artifact removal in PPG signal has been researched extensively [18]–[23]. It can also be noted that most of the published works focus on the detection and reduction of noise and artifacts in all other sensing modalities such as ECG, load cells, and PPG signals but not on BCG signals; thus, it has received very little attention. In [24], sleep and awake epochs are estimated via ballistocardiography using polyvinylidence fluoride film sensor on a mattress. Body movement epochs were identified by comparing the heart rate values to a threshold. These epochs were then used for estimating sleep efficiency and compared to PSG results. In [25], three signals were recorded to estimate BCG signal to noise ratio. ECG, BCG and motion signals were recorded while the subject was stationary as well as when there was movement. Then, all three signals were postprocessed to achieve two signal estimates: (1) BCG noise which was estimated from the BCG and ECG signals, and (2) motion noise derived from the motion signal. The correlation between BCG noise and motion noise estimates were used to calculate the BCG SNR. A load sensor based measurement of BCG signal was used in [26] for heartbeat, respiration measurements and identification of specific types of movement. Sivanantham [26] extracted 14 different features including variance from y-axis of the bed, trajectory length of the central mass points, average values of sensors, average diagonal load sensors energy and average percentage variance of each load sensor. These features were fed into a support vector machine (SVM) classifier to classify the specific type of movements such as hand, leg and all other movements. However, none of the prior efforts [24]–[26] attempted to recover the motion corrupted BCG signals, nor did they attempt reconstruct the BCG data in order to extract hear rate or B-B interval. Our objective is to use the reconstruction of motion corrupted BCG signal to extract useful information such as heart rate and respiration rate for further physiological sleep analysis especially in children with ASD.

B. CONTRIBUTIONS

This paper describes a comprehensive BCG signal analysis system that combines motion artifact detection and reduction methods for B-B interval estimation. Specifically, the interest is to evaluate usability and performance of a bed-based BCG acquisition/processing system for sleep analysis in children with ASD. The bed-based acquisition system includes four EMFi film sensors and ECG signals are recorded simultaneously. The BCG signals are first analyzed and motion corrupted frames are identified. Motion detection is based on a sequential detection algorithm where a sequential hypothesis test procedure is repeated until a decision is reached [27]. Using practical test data, we characterize the performance (probability of false alarm: P_{FA}, probability of detection: P_D) of our motion artifact detection method. As the second step in the process, we present a novel approach to reconstruct BCG frames from those portions of the data that have been identified to be clean using a prediction based autoregressive model and Wiener smoothing based estimation of the underlying BCG signal parameters. The estimated parameters are J-J interval, J-K amplitude, and the most significant frequency component in the BCG signal. We evaluate the proposed approach using nineteen hours of sleep (more than 40,000 frames) of sleep BCG data including both clean and motion corrupted ones. The fidelity of the reconstructed signal is determined by comparing the estimated B-B interval to reference values (ECG R-R interval) by using features such

as coverage and precision. The results indicate that for all film sensors, we achieve approximately 96% probability of detecting motion and high average coverage of 84% with over 90% precision for the reconstructed B-B intervals. Based on comparison to ECG R-R intervals as reference, it is also shown that Wiener smoothing based B-B interval estimation algorithm is more accurate than the AR model based approach. The proposed motion artifact processing system is a first of its kind developed and tested for bed-based BCG signals.

The remainder of the paper is organized as follows. Section II provides a general overview of the smart bed system and the bed-based BCG signal. The sequential method to identify motion artifacts in BCG signals is described in detail in section III. In section IV, model-based BCG signal tracking and estimation is presented. The results of the proposed algorithms are presented and discussed in section V.

II. BCG SIGNAL ANALYSIS

BCG measures the micro-movements of the body as a displacement, velocity or acceleration signal [28]. These movements are produced by body's recoil forces in response to a heartbeat. Fig. 1 shows two cycles of a ECG waveform along with BCG waveform in which the BCG extrema are named with consecutive letters from H to N for each cycle. The H-K waves form the ventricular systole and L-N waves occur during the diastole. The waves of the BCG signal are a combination of the forces created by the heart and blood flow. The I wave follows the ventricular systole. The recoil force created from blood direction changes towards the head is seen as a strong J wave in BCG signals and K wave is caused by the deceleration of blood flow. The interpretation of L-, M- and N- waves is more uncertain. The combination of all these waves represents the cyclic event of the heart beating. An ideal BCG heartbeat signal can be modeled as a sinusoid of frequency f_b windowed with a cosine window of length d as shown in Fig. 2 [29]. The heartbeat shape $w(t)$ corresponds to:

$$w(t) = A\sin(\frac{\pi t}{d}).\sin(2\pi f_b t)$$
$$\mathrm{A} = \frac{JK_{amp}}{2}$$
$$d = \frac{\mathrm{JJ_{int}}}{f_s}$$
$$f_b = d.f_c - (\frac{1}{2d}) \quad (1)$$

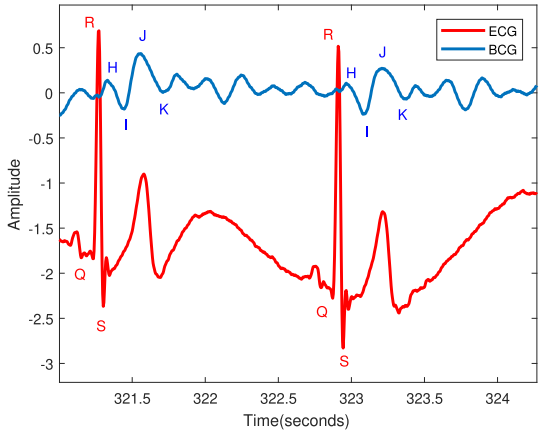

FIGURE 1. BCG and ECG signals of a two heart-cycle.

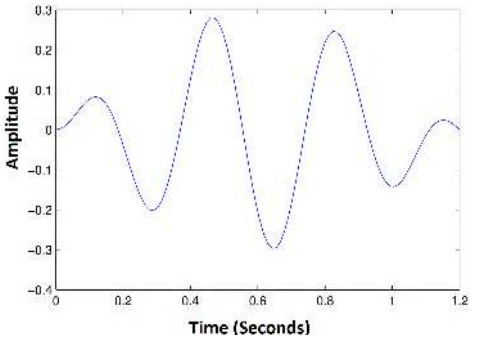

FIGURE 2. BCG signal of an ideal heartbeat [29].

where, the three parameters that influence $w(t)$ are J-K amplitude which is the amplitude of J-peak to K-peak of the corresponding BCG cycle, J-J interval which is the interval between two consecutive J peaks, and f_c which relates to the most significant frequency component in one BCG cycle. These three parameters that characterize the BCG signal change slowly over time and they are correlated across time. Therefore, if one can track the variation of these parameters through both clean and motion artifacted signal frames, it would be possible to reconstruct the BCG signal over time enabling the continuous monitoring of B-B interval/heart rate. We exploit this idea to design a motion artifact reduction strategy that is described in section IV. When a frame is detected as motion corrupted one, J-K amplitude, J-J interval, and the most significant frequency component of the previous (using AR model based prediction) frames or previous and future (using Wiener smoother based estimation) frames, are used as the basis for estimation of the new heartbeat frame.

A. BCG ACQUISITION SYSTEM

Several types of sensors can record the force signals or cardiac vibration signals generated by the heart if they are coupled to the body in one form or another. The most popular method for measuring the ballistocardiogram is by using a force plate or weighing scale and having the subject stand as still as they can to reduce motion artifacts. Other popular modalities include seat or chair-based systems [30], bed-based systems [24], [26], [31]–[35], and wearable systems [36], [37]. The bed-based modality makes the most sense for long-term monitoring and sleep quality assessment of severely disabled children. As it was mentioned in section I, wearable systems are not suitable for this type

of population, thus any type of wearable BCG system was not an option. Any BCG-based system needs to be extremely sensitive to pick up the small forces generated by the heart beating, and since the systems are designed to record mechanical vibrations, they are susceptible to motion artifacts that can completely overwhelm the BCG signal. Motion artifacts tend to be even more prevalent in children with ASD since they tend to suffer more from sleep disorders such as sleep apnea, sleepwalking, nightmares, and restless leg syndrome. A typical BCG signal corrupted with motion artifacts can be seen in Fig. 3. There is a clear need to reconstruct the corrupted BCG to extract the heart rate.

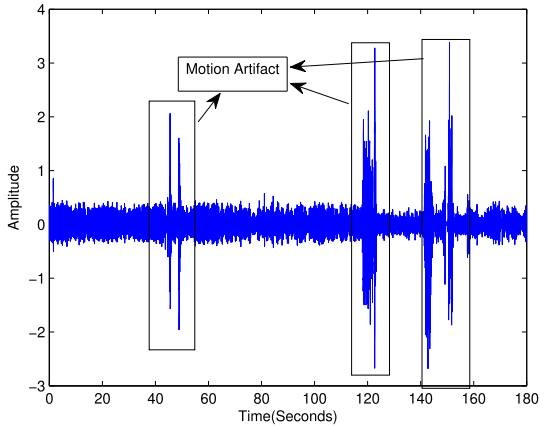

FIGURE 3. BCG signal with motion induced artifacts.

Our custom bed system includes four electromechanical films (EMFit; L series; 300 mm x 580 mm) and four load cells (TE Connectivity Measurement Specialties; FX1901-0001-0200-L). The sensors are hidden under the mattress and beneath the bed posts, so that the subject is not aware that any changes have been made to their environment. This is a critical aspect of our system, since autistic children are extremely sensitive to even small changes in their environment. The electromechanical films (EMFis) generate a proportional current in response to an applied changing force. The outputs from the EMFis are conditioned by analog circuitry before being connected to one channel of a National Instruments analog input module, NI 9220 (sixteen 16-bit differential channels). The signal conditioning circuit consists of a charge amplifier, a 2nd order active Sallen-Key low-pass filter with a cutoff frequency of 20 Hz, and a final non-inverting amplification stage. While the bed based BCG data is the only information required for sleep quality analysis, we collect ECG data just for validation purposes. As mentioned earlier, ECG data collection is invasive and not suited for long term monitoring. However, in this initial stage of validation using the gold standard of ECG is helpful to demonstrate the value of BCG based estimation of physiological parameters. An iWorx ETH-225 bioamplifier with an iWorx ECG module was used to collect the reference ECG data. The output of the ECG module was also connected to one of the NI 9220 analog input channels to gather the BCG and ECG data synchronously. The NI 9220 is connected to a NI 9184 Ethernet chassis. The entire NI acquisition system is controlled by a virtual instrument on a PC running LabVIEW version 14.0.1 which set the sampling rate to 250 Hz for each acquired signal. The virtual instrument does not apply any additional filtering before saving the data to a file on the PC. More details on the bed-system architecture under development at Kansas State University including a preliminary comparison of estimated BCG HBIs compared to the gold standard ECG R-R intervals can be found in [31] and [38]. This work focuses on utilizing the signals measured from the EMFi sensors to estimate the cardiac B-B intervals from a reconstructed BCG signal. Future work will involve an efficient, holistic measure of sleep quality by fusing the information available from all the sensors.

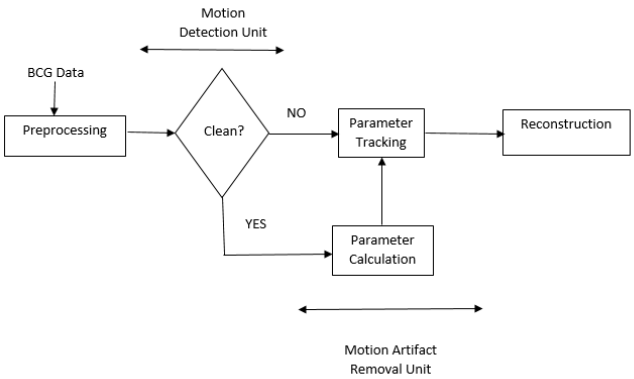

FIGURE 4. BCG signal motion artifact detection and reconstruction system.

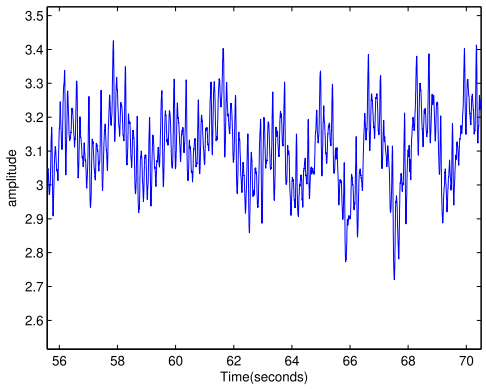

FIGURE 5. Acquired BCG Signal (with respiration).

The proposed BCG data processing system is illustrated in Fig. 4. Specifically, there are 3 steps including preprocessing, motion artifact detection unit and motion artifact removal unit. In the preprocessing step, low frequency content is removed via a Butterworth bandpass filter of order 6 (0.5-25 Hz). This filter is applied to the individual EMFi signals. The input and output of this filter for a sample input are illustrated in Fig. 5 and Fig. 6. After filtering, each BCG film signal is partitioned into short frames of equal length.

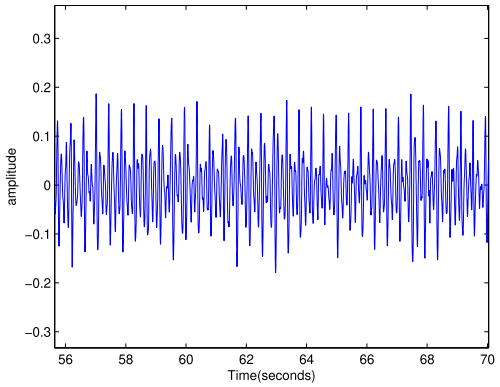

FIGURE 6. Filtered BCG Signal (without respiration).

In our implementation, frame length is fixed to 1s, similar to other efforts in this field [39]. This choice of frame size also helps preserve the shape of a single heartbeat for calculating physiological parameters that depend on B-B intervals. In the next step, each preprocessed frame is analyzed and a binary decision is made, indicating if the signal frame is clean or motion corrupted (details can be found in section III). If the data is found to be clean, no further cleansing actions are imposed, but if a frame is detected as motion corrupted one, it will be cleaned based on a parametric model-based reconstruction as discussed in section IV.

III. MOTION ARTIFACT DETECTION

The objective of the second step of the data processing system (Fig. 4) is to analyze the pre-processed BCG signal, to determine if the frames contain motion artifacts. The principle for detecting motion artifacts is presented in detail in our prior work [27] and is briefly described here. Since the preprocessed BCG signals serve as our measurements for sequential detection, it is important to first characterize the distribution of both clean and motion corrupted BCG signals. Our training data set (consisting of over 4000 frames for each subject) is used to fit a Gaussian distribution for clean and Laplace distribution for motion corrupted signals, respectively as illustrated in Fig. 7. The parameters (μ_0, σ_0^2- Clean; μ_1, b_1- motion-corrupted) of the fitted Gaussian and Laplace distributions are estimated for the four BCG film sensors. We then formulate a binary hypothesis testing problem where, H_0 corresponds to a clean signal frame, and H_1 corresponds to the case that the signal frame has motion artifacts. That is,

$$H_0 : y_i \sim P_0 = N(\mu_0, \sigma_0^2) \quad \text{[Clean]}$$
$$H_1 : y_i \sim P_1 = Laplace(\mu_1, b_1) \quad \text{[Motion-corrupted]} \quad (2)$$

Here, we consider a frame of length 1s of BCG data (y_i) each modeled as an iid Gaussian/Laplacian. The log-likelihood ratio for our binary hypothesis test corresponds to:

$$LLRT(\mathbf{y}) = log\frac{p(\mathbf{y}; H_1)}{p(\mathbf{y}; H_0)} = n.log(\frac{\sigma_0}{2b_1}) + \frac{\sum_{i=1}^{n}(y_i - \mu_0)^2}{2\sigma_0^2} - \frac{\sum_{i=1}^{n}|y_i - \mu_1|^2}{b_1},$$

This $LLRT(\mathbf{y})$ for each frame is then compared to two quantities- an upper threshold A and a lower threshold B, which are calculated as:

$$A = log(\frac{P_D}{P_{FA}}), \quad B = log(\frac{1 - P_D}{1 - P_{FA}}) \quad (3)$$

where, P_D is the desired probability of detection and P_{FA} is the desired probability of false alarm. As defined in equation (4) below, the final binary decision $\delta_S(y)$ is made based on the two pre-defined thresholds A and B :

$$\delta_S(y) = \begin{cases} 1 & \text{if } LLRT(\mathbf{y}) \geq A \\ \text{No Decision} & \text{if } B \leq LLRT(\mathbf{y}) \leq A, \\ 0 & \text{otherwise } LLRT(\mathbf{y}) \leq B, \end{cases} \quad (4)$$

Here, if $B \leq LLRT(\mathbf{y}) \leq A$, no decision is made while the next measurement is included in the test and the frame is shifted by one sample and a new likelihood ratio is computed. This hypothesis testing is a relatively easy procedure to implement and it is desirable for reasons besides its computational simplicity. The probabilities of detection and false alarm can be selected apriori and to a certain extent, the detection performance can be controlled. Furthermore, as illustrated in section V, the sequential detection approach is quite robust to model mismatches that may occur between training and test data.

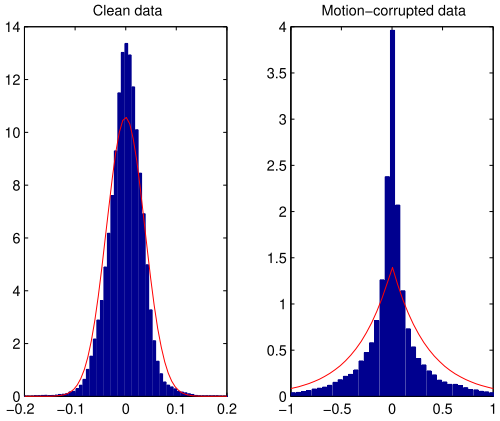

FIGURE 7. Histogram plots of clean and motion-corrupted frames with fitted Gaussian and Laplace distributions, respectively.

IV. MOTION ARTIFACT REMOVAL

While the motion artifact detection is completed and clean and motion frames are identified, the next step is to reconstruct the original BCG signal from the motion corrupted frames. As previously mentioned, each BCG signal parameter is correlated over time. This motivates the idea of tracking the BCG signal parameters through the motion impacted signal frames. A time series model that captures the dynamics of the signal parameters can help to estimate the parameters of both clean and motion corrupted signal frames. In this work, we suggest two different methods for parameter estimation namely: (1) AR model-based tracking and (2) Wiener

smoother based parameter estimation as discussed in following subsections.

A. PARAMETER TRACKING AND ESTIMATION

Once a frame is identified to have motion artifacts, artifact reduction algorithms are initiated to clean the signal. The most recent frame with clean data is identified. In the AR model-based approach, we track the variation of the BCG signal parameters in the two preceding clean frames in order to estimate the current frame signal parameters. On the other hand, a Wiener smoother estimator can be used to estimate the parameters of a motion artifacted signal frame by using both the past and future clean frame parameters. AR estimators can be used for online reconstruction even in the presence of non-stationarity while the Wiener smoother estimation approach assumes stationarity in the parameter dynamics. Details of these two algorithms are presented next.

1) AUTOREGRESSIVE MODEL

An AR model is used for predicting the current value of a variable of interest using a linear combination of its past values. The general definition for AR(p) model is as follows:

$$\theta_t = \sum_{i=1}^{p} C_i \theta_{t-i} + \epsilon_t \quad \epsilon_t \sim N(0, \sigma^2) \tag{5}$$

where, C_i are the auto-regression coefficients, θ_t is the series under investigation, p is the filter order, and ϵ_t is the Gaussian process noise. In our motion artifact removal strategy, the $\theta_t = (\theta_{t,1}, \quad \theta_{t,2}, \quad \theta_{t,3})$, where $\theta_{t,i}$ for $i = 1, 2, 3$ corresponds to BCG signal parameters namely: JK_{amp}, JJ_{int}, and f_c. These three parameters are identified using heartbeat information such as J and K peaks and the most significant frequency component. For fitting an AR model to each parameter, we use partial autocorrelation to identify the order of the corresponding AR model. Therefore, in the sample autocorrelation plot (see Fig. 8), we look for the delay where the partial autocorrelations essentially become zero. Placing a 95% confidence interval for statistical significance is helpful for this process. As illustrated in Fig. 8, the best model order for J-J interval parameter is AR(3). With the same procedure, we conclude that 2nd order AR model is appropriate for the other two BCG signal parameters. Once the model has been identified for each parameter, the AR model predictors can be obtained by finding the estimated coefficients for each parameter using training data.

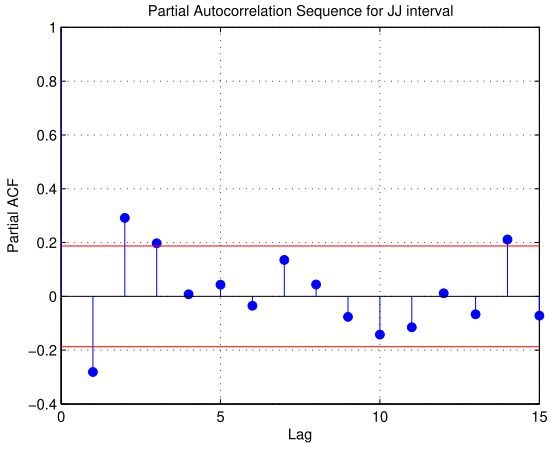

FIGURE 8. Partial autocorrelation plot for J-J interval parameter.

2) WIENER SMOOTHING

In this approach, we first uncover the underlying correlation over time that is exhibited by the BCG signal parameters. Fig. 9, for example, plots the autocorrelation function of the J-J interval parameter. This correlation can be used to estimate signal parameters in motion corrupted frames. In general, consider we have a set of samples θ_n coming from a jointly wide sense stationary (WSS) process (consider $\theta_n = (\theta_{n,1}, \quad \theta_{n,2}, \quad \theta_{n,3})$, where $\theta_{n,i}$ for $i = 1, 2, 3$ corresponds to BCG signal parameters at time n which are JK_{amp}, JJ_{int}, and f_c). The goal is to find the linear estimate of θ_n named as $\hat{\theta}_n$ using the L-most recent and L following samples of θ_n as:

$$\hat{\theta}_n = w_{opt}^T . \theta_n = \sum_{l=-L+1}^{L-1} w_{opt}(l)\theta_{n-l}, \quad n = 0, 1, \ldots \tag{6}$$

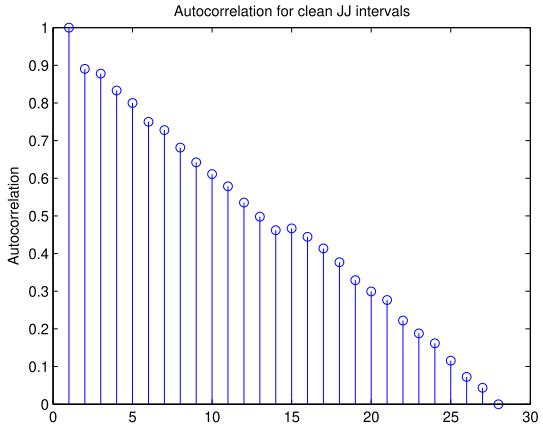

FIGURE 9. Autocorrelation for J-J interval parameters.

Here, w_{opt} corresponds to the optimal weights which is estimated using equation (7), and L is chosen based on the number of samples that exhibit significant autocorrelation (calculated using training data). In Fig. 9, for example, if we set a threshold of 0.2 for the autocorrelation, then $L = 20$; if the threshold is 0.1, then $L = 25$. We need to determine the coefficients $w_{opt}(l)$ that minimize the mean squared error (MSE) between $\hat{\theta}_n$ and θ_n. Based on Wiener-Hopf smoothing equations, for computing the optimal smoother weights w_{opt} corresponds to:

$$w_{opt} = R_\theta^{-1} . r_{\theta\theta_l} \tag{7}$$

where, $R_\theta = E[\theta(n).\theta^T(n)]$ and $r_{\theta\theta_l} = E[\theta(n).\theta(n-l)]$ are the input autocorrelation matrix and cross correlation vector, respectively. In this study, we use both past and future values

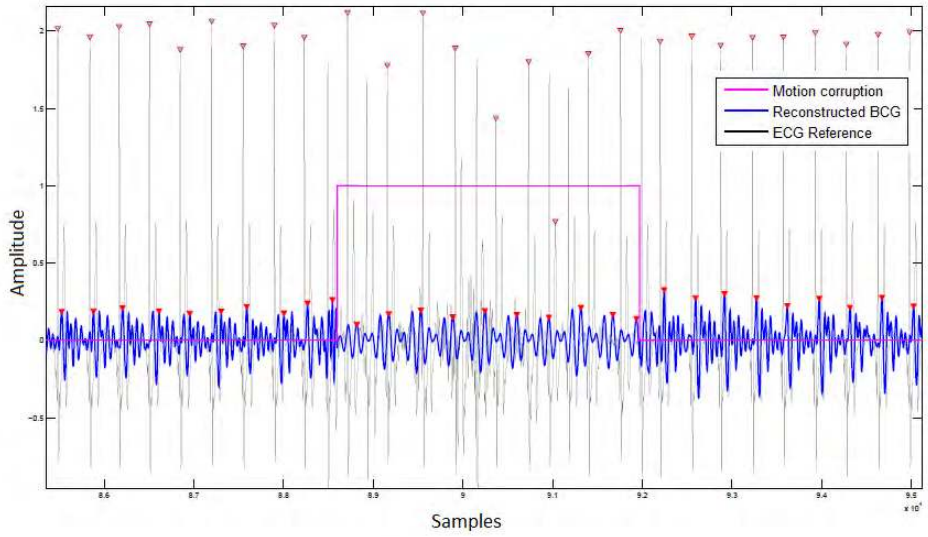

FIGURE 10. Peak Detection in both Recovered BCG and reference ECG data (results from BCG film0).

of BCG signal parameters to predict the current parameter values. Therefore, $r_{\theta\theta_l}$ is built based on the lag values of past/future frames with the present one that is to be estimated. These two matrices can be estimated with example autocorrelation function (ACF)s evaluated using the training data. Once the optimal coefficients w_{opt} are estimated, the Wiener model for each BCG parameter can be obtained using equation (7).

Once the BCG parameters are evaluated for the motion corrupted frames, the BCG signal is reconstructed using equation (1) $\hat{w(t)} = \hat{A}\sin(\frac{\pi t}{\hat{d}}).\sin(2\pi\hat{f}_b t)$ (see section II).

V. RESULTS AND DISCUSSION

The proposed motion detection and removal algorithms are tested and validated with data collected from three subjects providing nineteen hours of sleep with corresponding bed-based BCG data. All BCG film sensor data was analyzed individually. Since the results were consistent across all four film sensors, we present the findings from the analysis of Film0. ECG signals are used to establish ground truth values of B-B interval specifically. As a gold standard for comparison, R-peak to R-peak intervals in the ECG signals, which were sampled at 250 Hz and band-limited to 0.5-25 Hz are used [40]. It is important to note that while ECG R-peak detection is also susceptible to motion, the detected R-peaks in [40] were determined (experimentally) to be more robust than other R-peak detection approaches (Lee *et al.* and Lydon *et al.*) for our system.

TABLE 1. Performance of sequential motion detection method for four film sensors (results from BCG film0).

Probabilities	Film0	Film1	Film2	Film3
P_d	0.96	0.94	0.95	0.94
P_f	0.065	0.062	0.023	0.014

We first apply the sequential detection procedure outlined earlier to the test data sets and evaluate the lower and upper thresholds by setting $P_D = 0.9$, $P_{FA} = 0.1$. The actual performance based on a comparison with ground truth data is presented in Table 1. In this case, ground truth data was generated by examining infrared (IR) images of the subject by using thermal camera and manually identifying motion instances and durations. The frames were fed to a motion detection unit in order to detect the presence of motion artifact and the result for this part of the implementation is binary decisions for all of the BCG frames. The result of motion detection are brought here as probability of detection and false alarm as in Table 1. From Table 1, it is evident that the proposed sequential detection approach is very effective in discriminating between clean and motion corrupted frames (with nearly 96% accuracy) for all four film sensors. As the next step, when the frames are detected as corrupted or clean, the reconstructing procedure using the methods in section IV are implemented. We applied AR and Wiener filter approaches on the frames identified as motion-corrupted and reconstructed those frames. Then, we estimated B-B intervals in the new BCG frames, as well as in the corresponding reference ECG frames. The results of the procedure are illustrated in Tables 2 and 3 for all three subjects (named as B-B interval (motion)). Additionally, for a complete performance evaluation, we also use both methods to predict the parameters for frames that are detected as clean in the previous step (motion artifact detection) and the corresponding B-B interval (the corresponding results for clean BCG frame reconstruction are mentioned in Tables 2 and 3 as B-B interval (clean)).

The quality of the reconstructed signal for both clean or motion corrupted frames, is captured by the accuracy of the estimated heartbeat events and heartbeat interval lengths using a synchronized ECG as benchmark.

TABLE 2. B-B Interval performance results of the proposed AR algorithm (results from BCG film0).

Subjects	Data	Mean BCG (s)	Mean ECG (s)	Coverage (%)	Precision (%)
subject 1	B-B interval (clean)	1.07	1.03	87.04	93.41
	B-B interval (Motion)	0.97	1.08	83.32	92.21
subject 2	B-B interval (clean)	1.11	1.23	84.93	93.2
	B-B interval (Motion)	1.12	1.41	82.64	95.3
subject 3	B-B interval (clean)	0.88	0.93	80.24	91.8
	B-B interval (Motion)	1.21	1.22	79.62	90.2
Total average	B-B interval (clean)	1.02	1.06	84.07	92.8
	B-B interval (Motion)	1.1	1.23	81.86	92.57

TABLE 3. B-B Interval performance results of the proposed Wiener smoother algorithm (results from BCG film0).

Subjects	Data	Mean BCG (s)	Mean ECG (s)	Coverage (%)	Precision (%)
subject 1	B-B interval (clean)	1.01	1.03	91.43	95.39
	B-B interval (Motion)	1.09	1.08	88.27	94.33
subject 2	B-B interval (clean)	1.38	1.23	89.22	96.3
	B-B interval (Motion)	1.52	1.41	87.09	95.83
subject 3	B-B interval (clean)	0.99	0.93	84.53	94.2
	B-B interval (Motion)	1.18	1.22	83.22	93.27
Total average	B-B interval (clean)	1.12	1.06	88.39	95.29
	B-B interval (Motion)	1.26	1.23	86.19	94.47

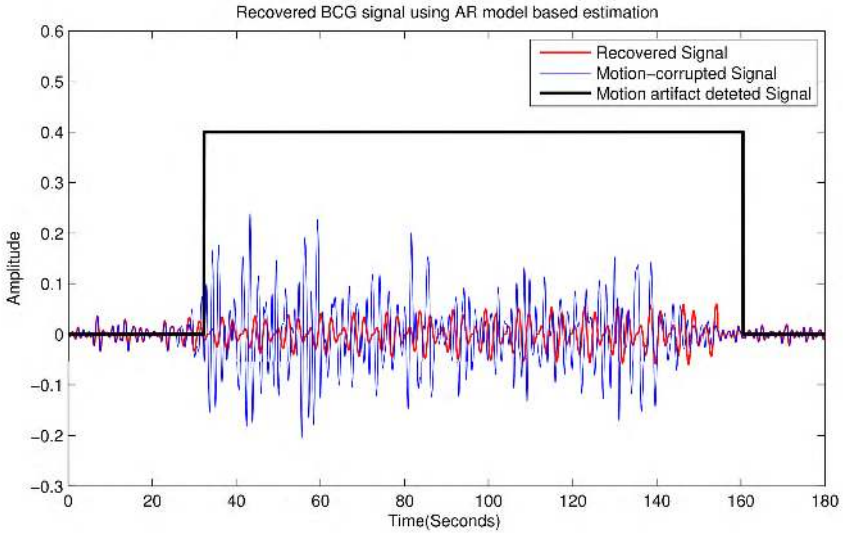

FIGURE 11. Reconstructed BCG signals using AR parametric model estimation (results from BCG film0).

The differences between BCG J-J intervals and ECG R-R intervals from three subjects and each parameter estimation method are presented in Tables 2 and 3. The performance of the proposed algorithm is evaluated with parameters including *coverage* and *precision* [39]. Coverage is defined as the ratio of number of detected BCG intervals and number of detected ECG intervals. Then these detected intervals are classified as correct and incorrect ones to measure precision as the ratio of correct ones over all intervals. According to the coverage metric, 91.43% of the B-B intervals have been detected with more than 90% of precision. The Wiener smoothing approach provides a better B-B interval estimate than the AR approach. This can be attributed to the fact that Wiener smoothing uses both past and future frames for estimation but the AR model prediction is based exclusively on the past values. However, it is important to remember that Wiener smoothing relies on the assumption of stationarity of the underlying parameter dynamics.

Fig. 10 illustrates an example of peak detection for both ECG signal (black plot) and recovered BCG signal (blue plot) using Wiener smoother estimation method. The pink line shows the motion corrupted part in BCG and the blue line shows the reconstructed heartbeats using the proposed algorithm. This figure presents the alignment of the reconstructed BCG J-peaks with the corresponding ECG R-peaks. Here, the goal is to show how the proposed motion reconstruction algorithm performs by comparing the identified J-peaks with the reference R-peaks. The peak alignment indicates that the algorithm is effective in recovering the heartbeat via BCG data and the B-B intervals are well aligned with the reference ECG data. Fig. 11 shows an example of motion reconstruction using the AR approach and motion detection using sequential detection method.

Limitations of the study include the small numbers of subjects in the analysis. Although the number of subjects is not large, we have extensive night time data for each subject. Given the focus of this work is to showcase new motion detection and removal strategies, the more than 40,000 sleep frames offer a solid foundation for testing and validation. It is worth mentioning that a long term (more than 5 months) data collection in Heartspring, Wichita, KS is in progress for two children with autism spectrum disorder for future analysis. Another limitation of the study is that subjects are not impacted by any kind of cardiac issues such as arrythmia. Future work will study how performance of the methods is impacted by considering subjects with different types of cardiac problems.

VI. CONCLUSIONS

In this paper, we present a simple yet efficient method for detection and removal of motion artifact in BCG signals. In the detection unit, a sequential decision rule is designed in which successive data frames are compared to upper and lower thresholds to achieve a desired probability of detection and false alarm. If any frame is detected as clean, its three parameters including J-K amplitude, J-J interval, and the most significant frequency component are calculated. If the signal frame is detected as being motion-corrupted, the three signal parameters are estimated using an auto-regressive (AR) model-based tracking or a Wiener smoother. The efficiency of the methods are illustrated using B-B interval comparison with ECG data based on over nineteen hours of sleep obtained from multiple subjects. The comparisons with ECG reference data indicate that the algorithms can effectively help to detect and remove the motion artifacted BCG signals based on sequential detection and model-based parametric tracking and reconstruction.

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