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A modified approach of peak extraction from BCG for heart rate estimation

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Abstract. We propose a novel method for detecting a single heartbeat interval from ballistocardiogram (BCG) from healthy subjects. An inconspicuous tilt sensor is embedded in the mattress to record a robust estimate of the local beat interval. The sensor could measure body movements caused by cardiac activity. Compared to many existing methods, this new method provides real-time and accurate heart rate estimation for all normal data and most both artifacts and anamorphic data on a beat-by-beat basis. The consistency of the proposed method with the ECG reference has been evaluated. In this data set containing approximately 15,000 heart beats, records of 10 subjects achieved an average beat interval error of 0.88% with a coverage rate of 96.94%.

1. Introduction

Heart attack is one of the most common causes of death. Ballistocardiogram (BCG) [2] is a method of recording the vibrations of the body caused by cardiac activity. Detection of real-time heart rate with BCG signal can closely observe changes in the heart, detect abnormalities in the heart in time, and minimize the risk of morbidity. ECG-based techniques that require additional electrodes on the body, it is not suitable for long-term use due to the stimulating effects of the electrodes on the human body. The bed-based BCG technology is a comfortable, non-sensory method of detecting heart function.

Heartbeat interval estimates from BCG data have been studied in recent years [3] [4] [5]. For BCG data with standard waveforms (e.g. fig 1(a) red line), the heartbeat can be identified by traditional J peak detection [1]. However, due to the trouble of redundant BCG periods or non-BCG periods, the causes thereof include motion artifacts, BCG signal oscillations, and other factors. Using a tilt sensor to track heart rate during sleep presents several challenges. First, the subject's body is not in direct contact with the sensor, so the observed BCG signal is very weak, which makes the signal highly susceptible to noise. Fig 1(a)blue line shows the effect of one subject's BCG cycle signal on the amplitude of J peak signal (the location of the heartbeat) when it is disturbed. Secondly, during the test, the subject's lying position may occasionally change, causing indirect contact between the subject and the tilt sensor to be unstable, resulting in severe noise, fig 1(b) shows the change in amplitude of the BCG signal when the subject's posture changes. Therefore, algorithms based on traditional J peak detection are not very practical in many cases.

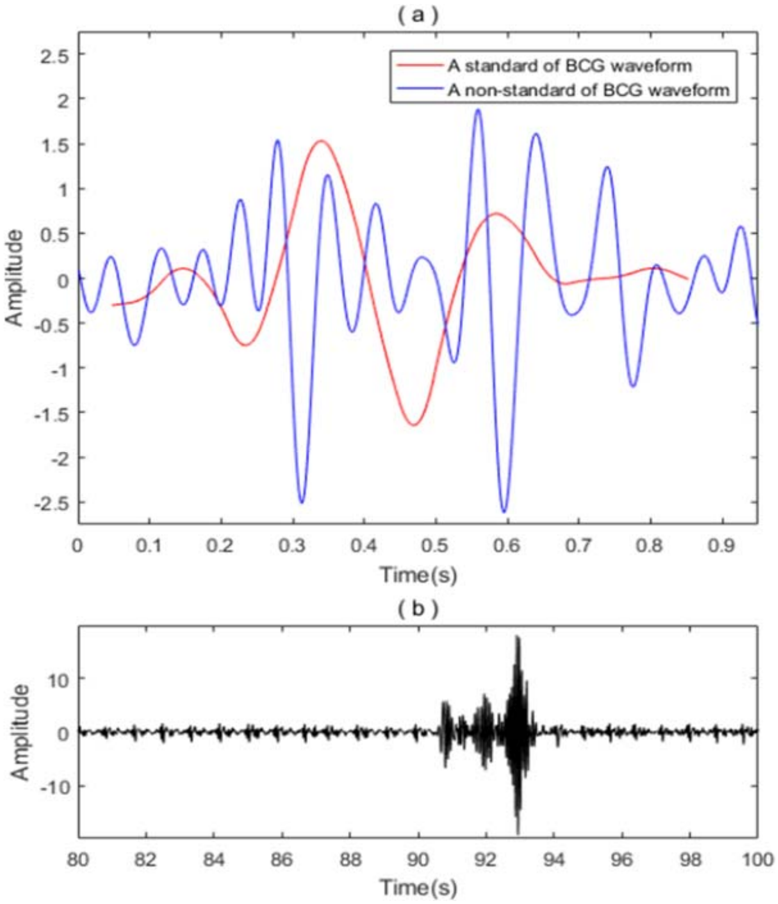

Figure 1. (a) Red line: Standard BCG waveform. (a) Blue line: An example of a non-standard BCG waveform. (b) Noise when the subject's posture changes

In order to improve the accuracy of heart rate measurement, many methods have been proposed to eliminate motion- induced noise, including standard digital filter [6], linear phase filter [7], and wavelet transform [8]. However, most of the existing methods are mainly designed for breathing and subtle body movements. When the signal from the sensor is weak or even lost due to motion, its perform poorly because the noise caused by unpredictable motion is much more complicated than the small noise such as breathing. Although there are some methods for reducing noise due to motion, they rely on complex signal processing algorithms.

Based on the above purposes, this paper proposes a new J peak detection algorithm to solve the extraction of physiological parameters of BCG signals from new sensors. And for the artifact data segment, we propose a mathematical model to estimate approximately the heartbeat position of the segment of data.

The structure of this paper is as follows. In Section II, we describe the system design and algorithms. In Section III, we evaluated the performance of the algorithm. Finally, we summarize this paper in Section IV.

2. METHOD

2.1. *Design of system*

For the purposes of this study, BCG data (e.g. fig 2) were obtained using a tilt sensor (model: SCA61T-FAHH1G, sensitivity 70 mV/) embedded in the mattress when a person was resting in bed. Instrumented slats were placed under the subject's chest to best record cardiopulmonary activity. A normal mattress is placed on top of the slats. Data was acquired by a 12-bit analog-to-digital converter with a 1 kHz sampling rate. The final signal represents the beat-to-beat time response (ballistocardiogram, BCG) due to blood exchange of the subject. The three-lead electrocardiogram (ECG, model: AD8232, FS=1000 Hz) was simultaneously recorded as standard reference data for experimental verification.

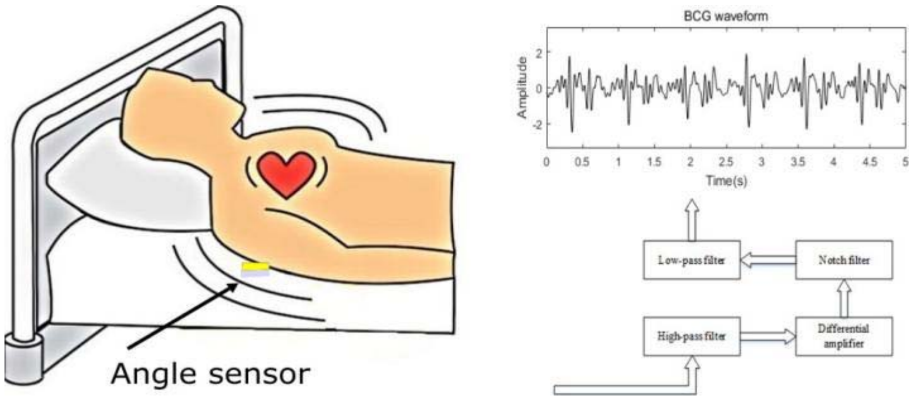

Figure 2. System of BCG measurement

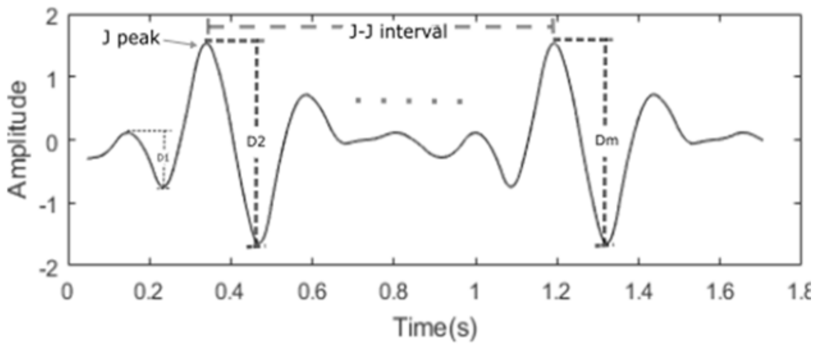

Figure 3. An example of waveform

2.2. Preprocessing

The subject lies on a bed equipped with sensors, and the body's force on the bed during exercise, breathing, and heart pumping is converted by the sensor system into an AC voltage output with DC offset; first, high-pass filtering is performed (The cutoff frequency is 3Hz) to remove the DC component generated by the bed and the body; after differential amplification, 50Hz notch and low-pass filtering (cutoff frequency is 11Hz) to remove power frequency interference and high frequency noise to obtain BCG signal (e.g. fig 2).

2.3. Basic algorithm

In the following, we propose a heartbeat algorithm is that detection of the value of the maximum difference between local peaks and troughs which corresponding to the BCG peak mode of a single heartbeat. An overview of the proposed algorithm is given by the flow chart shown by fig 4.

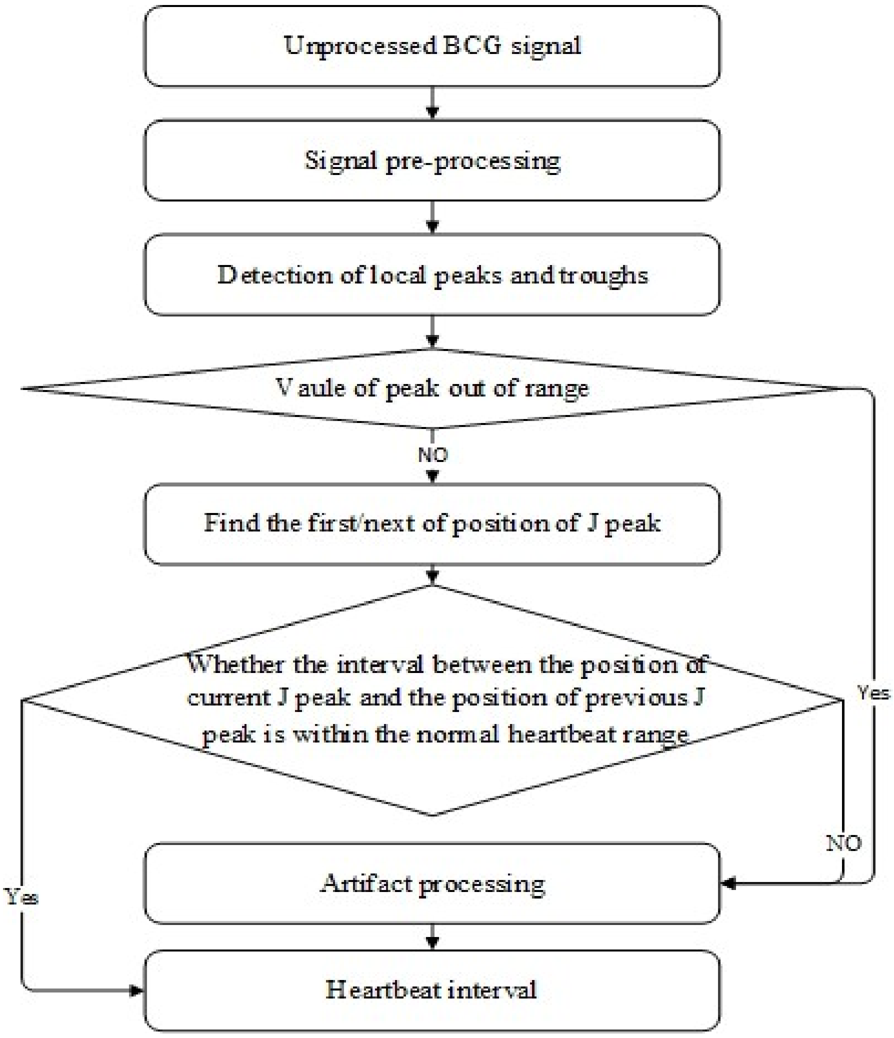

Figure 4. Algorithm flow

Let the pre-processed signal be represented as x[n], and iteratively move the short analysis window on the signal. The length of the window is selected based on the antecedent knowledge of the expected range of normal human heart rate (40 − 140bpm). According to the heart rate formula:

$$HR = 60/T_{\text{heartbeat interval}} \tag{1}$$

Define the heartbeat interval as [Tmin, Tmax]. Based on experience, we will analyze the window interval as [Ni, Ni+2·Tmin·Fs] to ensure at least one heartbeat is detected in this interval, Ni indicates the sample center. In steps i and ii, 2·Tmin·Fs iterations for x [Ni, Ni+2·Tmin·Fs]:

I Find all the peaks P (local maximum values) in the range and record their position:

$$P[n].v = x[n] \quad \text{and} \quad P[n].i = n \tag{2}$$

Which meets the conditions:

$$x[n] > x[n+1] \quad \text{or} \quad x[n] \geq x[n-1] \tag{3}$$

Find all the trough T (local minimum values) in the range and record their position:

$$T[n].v = x[n] \text{ and } T[n].i = n \tag{4}$$

Which meets the conditions:

$$x[n] < x[n+1] \text{ or } x[n] \leq x[n-1] \tag{5}$$

Ii calculate the maximum amplitude (Vmax) of the analysis window and check if Vmax is within a given threshold. Since the amplitude variation produced by motion artifacts typically has a much higher than the undistorted BCG, if Vmax is within the threshold, a valid signal in the analysis window is assumed. Otherwise, the window is treated as an invalid window and the algorithm jumps to the step (v).

Iii As shown in fig 3, for peaks with varying slopes, the peaks and troughs are one-to-one. For the peak and trough data recorded in step i, assume the length of the array of structures (P&T) is M, M iterations for both P [0, M-1] and T [0, M-1]:

Find the value of maximum difference (Max) between the peak and the trough (next to the peak), and record its position:

$$\begin{cases} Max[j].v = P[j].v - T[j].v \\ Max[j].i = P[n].i \end{cases} \tag{6}$$

Which meets the conditions:

$$\begin{aligned} &Max[j].v > P[j].v - T[j].v \\ \text{or } &Max[j].v \geq P[j].v - T[j].v \end{aligned} \tag{7}$$

IV Whether the absolute difference value (which is the J-J interval) between the position of the maximum difference(Max[j].i) calculated this time and the position(Max[j-1].i) at previous time is within the range of [Tmin, Tmax]. If so, the algorithm jumps to the step (vi), if not, the window is invalid and the algorithm continues with the step (v).

V For motion artifacts that cause complete distortion of the signal, there is currently no better way to handle the data lost by these signals. Because the signal-to-noise ratio is significantly reduced when the subject is performing a large motion on the bed, it is impossible to make a reliable beat interval estimation in a few seconds in this case. For people in a calm lying position, we believe that both the heart rate changes will not be too great in a few seconds and the continuous heartbeat interval should be regular in this case. Our experiments do not fully and accurately estimate the heartbeat interval under artifacts. Our goal is to minimize errors when data is not available. Fig 5 shows the heartbeat interval of the subject's continuous standard ECG signal in 3 minutes when the subject are at calm rest; we draw it into a curve and smooth it, we found that in a short time (about 10-20 sub-heartbeat interval), the curve is approximately equal to the superposition of a slightly inclined straight line and a sinusoid with absolute values:

$$y = (a \cdot t + b) + (A \cdot |\sin(\omega in(+\theta))|) \tag{8}$$

In the invalid window, we have recorded the recently 20 times heartbeat interval data and draw a coordinate graph to determine the approximate curve equation. We estimate the heartbeat interval of the window according to this curve equation.

VI The heartbeat interval calculated from the step (iv) or the step (v) yields the real-time heart rate parameter HR according to the formula (1).

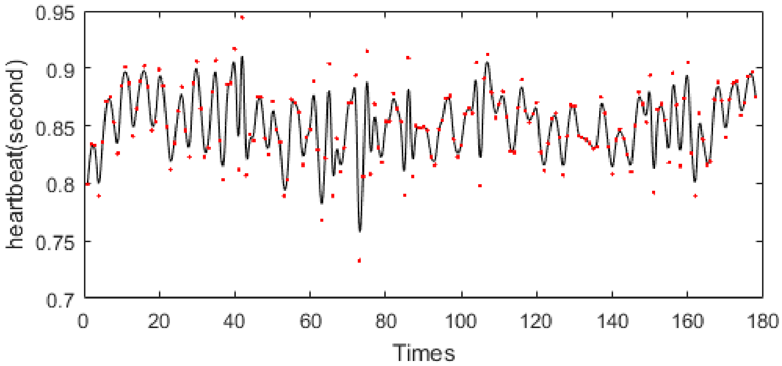

Figure 5. The data of heartbeat interval from ECG detection and waveform which has smoothed filtering; the x-axis is the number of heartbeats and the y-axis is time of the heartbeat interval.

3. Result

In this section, we analyze the performance of the proposed method from BCG signals obtained from an inconspicuous bed-based tilt sensor. Analysis was performed using MATLAB 2016a (The Math works, Natick, MA). Our implementation of the proposed algorithm enables real-time processing of data in 16-bit or 32-bit embedded processors.

The following performance indicators were analyzed using data from 10 healthy volunteers from the School of Computer Science and Technology, Hangzhou dianzi University(8 males, 2 females, age: 22±3). For each volunteer, the three-lead ECG (AD8232, Analog Devices, and MA) was filtered through a second-order high-pass filter to extract the R-R interval as the gold standard reference [10]. A single high-precision single- axis tilt sensor (SCA61T-FAHH1G, VTI, and JP) is installed at the bottom of the normal mattress in which close to the position of a person's chest. Fig 2 shows a schematic of the measurement system. The sensor produces a signal that is proportional to the force of human breathing, motion, and heartbeat in the horizontal direction of the sensor. The sensor is placed in the location on the subject's chest to record the heart vibration (BCG) and respiratory motion of the person lying on the bed. The performance of the proposed algorithm for heartbeat intervals is measured by calculating the following error statistic. Calculate each J-J interval (BCG) obtained by the algorithm, determines the method proposed by [10] to obtain the standard R-R interval (ECG), count the number of J-J and R-R intervals (J-J/R-R) and calculate the coverage (CR), the coverage indicates the percentage of between the J-J interval estimated by the proposed method and the number of reference R- R intervals; Statistical false positives (maximum correlation lags more than 100 milliseconds) ,false negatives (number of missed heartbeats) and their proportion (FP &FN); statistics and calculation of the average beat-to-beat interval error (E) of the J-J interval relative to R-R interval and calculate the absolute average interval error (Eabs).

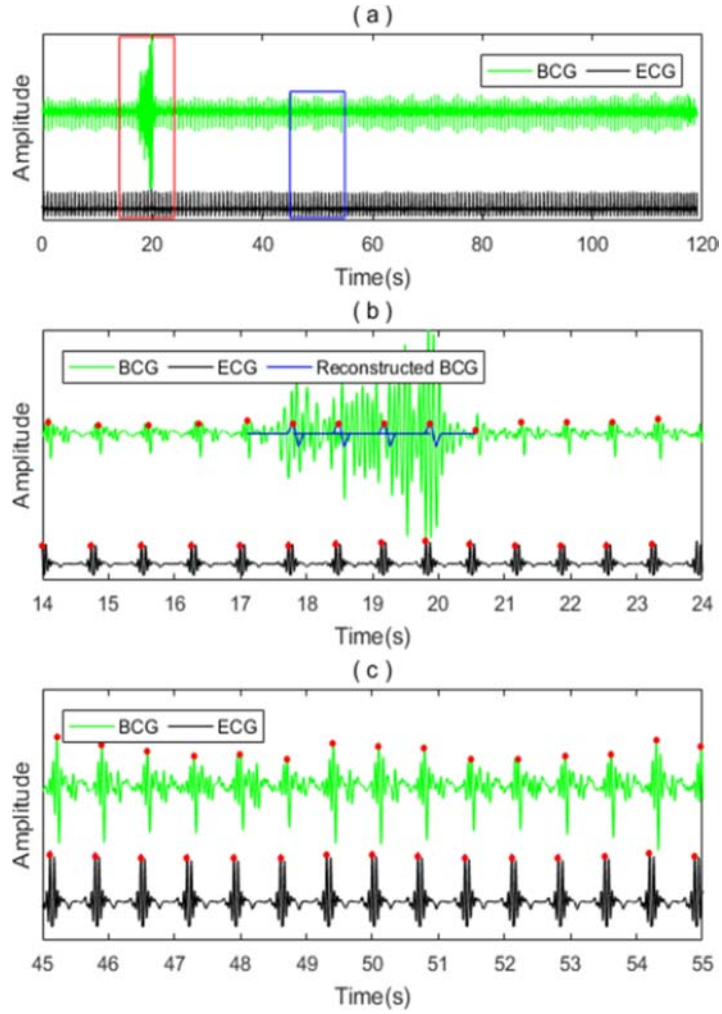

Figure 6. (a) Is the sample figure of both BCG and lead ECG of the subject M1 within 2 minutes. (b) Is a sample figure which containing artifacts as showing in red box inside (a). (c) Is a sample figure in normal testing conditions as showing in the blue box in (a).

Fig 6 shows a partial test example of subject M1. The part of the waveform that is prominent in the green line represents the artifact generated by the motion of the subject. The red dot marks in fig 6(b) & (c) represents the heartbeat position tracked, and the blue line represents the reconstruction of artifacts according to the proposed algorithm. Since the BCG signal has a delay relative to the ECG signal for a period of time, in order to achieve data synchronization and calculation error statistics, we empirically determine the reference and the time interval with the highest probability in the range of 0-200 milliseconds.

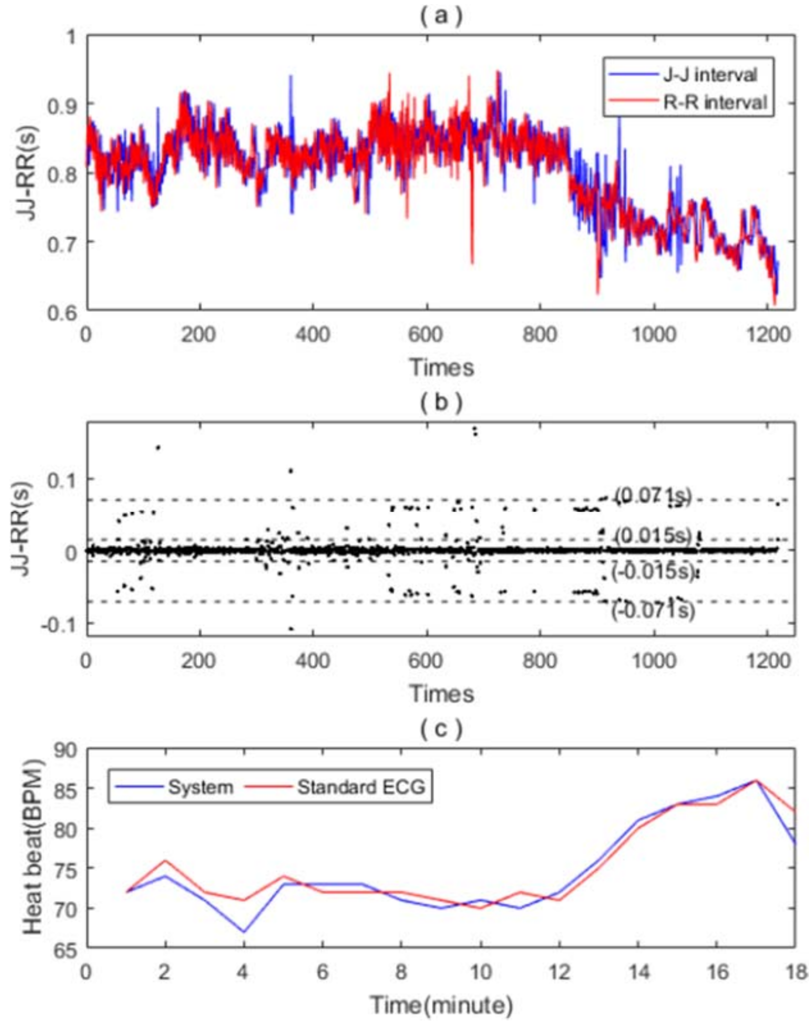

Figure 7. (a) Is a sample figure of the subject M1, which contains both the J-J interval for the BCG testing and the R-R interval for the ECG testing over 1300 times in approximately 20 minutes. (b) Is the Bland-Altman diagram of (a). (c) Is a sample figure of the subject M1, which contains the change of average heart rate at one minute of both BCG and ECG.

Fig 7(a) shows a comparison of J-J intervals and R-R intervals of subject M1 within 18.91 minutes. It can be seen that in most cases, the blue and red lines are almost coincident. The partially highlighted glitch in the blue line is the partial J-J interval estimated by the proposed algorithm when artifacts or data distortions are generated. Fig 7(b) shows the modified Bland-Altman diagram [9] from the beat-to-beat interval error of subject M1, which shows that the error of 99% of the interval error lies between 71ms, the error of 95% is between 15ms. Fig 7(c) shows the average heart rate change (the number of heartbeats detected within one minute) of subject M1 under the proposed algorithm and reference ECG. It can be seen from the figure that the estimated heart rate of the proposed algorithm compared with the reference ECG have an error range of 2 bpm. Overall, good agreement between the beat-by beat intervals of ECG and BCG can be observed.

The table I shows the performance of the proposed algorithm on the individual records on each individual. The average error and coverage can be achieved at 0.88% and 96.93%, respectively. The false negative rate and coverage ratio are relative. As the artifact length of different subjects increases/decreases, the missed heartbeat test (false negative) increases/decreases and the coverage decreases/increases. Table I shows the difference between mean and absolute error, coverage, false negative rate and false positive rate between different subjects. The reduced coverage can be attributed to the sensitivity of BCG to motion artifacts (e.g. subject 5&8). Due to the synchronization with the reference data, our method is only suitable for processing short-lived artifacts, and reliable beat-to-beat interval estimation cannot be performed for the latter part of the longer artifact data. Although our method provides accurate heart rate estimation for most BCG signals, if artifacts and data distortions cause our method to get the current heartbeat position incorrectly, or significantly different from the actual one, this will not only lead to the current estimation of the J-J interval increases/decreases and leads to an estimated decrease/increase in the next J-J interval, which in turn increases the false positive rate. Therefore our method may be unreliable in this case (e.g. subjects 2, 5, 8, 9). But what is important is that the absolute interval error level is still in the lower unit percentage range, and our approach is clearly able to keep the error within very acceptable limits.

In addition, we used the same data set to evaluate the performance of the traditional peak detection method proposed in [1] (ignoring artifact data);it can find local peaks in four sub-intervals over a period of time and select the largest peak from these local peaks as the J peak, along with some rejection rules. The table II shows the result. From the average false negative rate, the proposed method is 3.05%, and the [1] method that ignores the artifact is 5.84%, which indicates that the artifact ratio is about 5.84%, which reflects our the proposed method reconstructs most of the artifact data and derives heart rate parameters from it. Our method coverage, average false positive rate, mean error and average absolute interval error are 96.94%, 1.02%, 0.88% and 6.84ms, respectively, which indicates that compared to [1], we proposed the J-J interval deviation obtained by the method is smaller, with higher coverage and better overall accuracy. Overall our method is better than [1].

Table 1. The Performance of the Proposed Algorithm

Sub. NO.	Dur. [min]	J-J/R-R [piece]	CR [%]	FP [%]	FN [%]	E [%]	E_{abs} [ms]
1	18.92	1389/1441	96.39	0.28	3.61	0.79	6.19
2	21.16	1471/1530	96.14	1.44	3.86	1.05	8.5
3	21.24	1643/1682	97.68	0.71	2.32	0.56	4.19
4	21.26	1599/1635	97.8	0.73	2.2	0.49	3.82
5	19.36	1405/1471	95.51	1.5	4.49	1.22	9.59
6	21.25	1575/1601	98.38	0.56	1.62	0.71	5.62
7	17.6	1331/1382	96.31	0.43	3.69	0.5	3.82
8	19.84	1467/1545	94.95	2.33	5.05	1.72	13.53
9	18.79	1455/1480	98.31	1.42	1.69	1.19	9.1
10	21.35	1631/1665	97.96	0.84	2.04	0.53	4.13
Avg.	20.07	1496/1543	96.94	1.02	3.05	0.88	6.84

4. Conclusion

A new algorithm for estimating BCG beat heart rate is proposed. The proposed algorithm derives information about the heartbeat mode based on the particularity of extracting the J peak of the BCG signal. The estimated heartbeat position is obtained by finding the position of the value of the maximum difference between adjacent both peaks and troughs in the local BCG signal segment to obtain a heart rate parameter. For the artifact data segment, we propose a mathematical model to estimate approximately the heartbeat position of the segment of data.

To assess the quality of the outcome of the beat-beat heart rate estimate, our method was evaluated in a BCG signal about 15,000 heartbeats of nearly 200 minutes obtained from 10 subjects in a laboratory environment. A good agreement between the output of the proposed method and the gold standard can be observed. These results also show that the proposed method maintains a lower error level and higher coverage even in the presence of artifacts and noise conditions. We also compared the proposed method with the methods known in the literature and the results were good.

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Table 2. The Performance of the Traditional Algorithm of J Peak Detection

Sub. NO.	Dur. [min]	J-J/R-R [piece]	CR [%]	FP [%]	FN [%]	E [%]	E_{abs} [ms]
1	18.95	1342/1439	93.26	3.75	6.74	2.61	21.51
2	21.16	1435/1529	93.85	5.17	6.15	2.86	23.26
3	21.2	1574/1679	93.75	6.61	6.25	3.49	26.71
4	21.25	1568/1634	95.96	2.51	4.04	1.51	11.84
5	19.37	1356/1471	92.18	3.13	7.82	2.09	16.9
6	21.26	1534/1596	96.12	3.88	3.88	2.55	20.63
7	17.6	1294/1381	93.7	6.3	6.3	3.02	23.67
8	19.84	1414/1545	91.52	5.63	8.48	3.37	26.7
9	18.8	1406/1479	95.06	2.97	4.94	2.14	16.73
10	21.36	1602/1665	96.22	3.96	3.78	2.18	16.93
Avg.	20.07	1453/1542	94.16	4.39	5.84	2.58	20.48

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