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Heart Rate Estimation from Ballistocardiogram Using Hilbert Transform and Viterbi Decoding

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***Abstract*—This paper presents a robust algorithm to estimate heart rate (HR) from ballistocardiogram (BCG). The BCG signal can be easily acquired from the vibration or force sensor embedded in a chair or a mattress without any electrode attached to body. The algorithm employs the Hilbert Transform to reveal the frequency content of J-peak in BCG signal. The Viterbi decoding (VD) is used to estimate HR by finding the most likely path through time-frequency state-space plane. The performance of the proposed algorithm is evaluated by BCG recordings from 10 subjects. Mean absolute error (MAE) of 1.35 beats per minute (BPM) and standard deviation of absolute error (STD) of 1.99 BPM are obtained. Pearson correlation coefficient between estimated HR and true HR of 0.94 is also achieved.**

***Index Terms*—Ballistocardiogram, heart rate, Hilbert Transform, Viterbi decoding**

I. Introduction

Cardiovascular Disease (CVD) is the highest prevalence factor of the death in 2013, accounting for 31.5% of the global death [1]. 43.9% of the US adults are predicted to have some types of CVD. Heart rate (HR), as an important indicator of CVD, provides basic information of the health condition. Thereby, a convenient and obstructive system for HR monitoring plays an essential role in the prevention and early detection of CVD.

The most commonly employed signal for HR monitoring is electrocardiogram (ECG), which is a recording of the time-dependent voltage measured by electrodes attached to the body. ECG based systems are inconvenient and uncomfortable to use because the skin-electrode interface may cause skin irritation. The ballistocardiogram (BCG), on the other hand, records the movements of human body generated by blood being ejected and moved in the large vessels. It can be measured using instrumented chairs, weighing scales, beds and force plates [2], all of which can be installed in patient's homes. Compared the user experience of ECG and BCG, BCG offers clear advantages in terms of easy of use, comfort level, and cost. Therefore, BCG based systems are potential candidates for HR monitoring at home or community center.

There are a variety of methods to measure HR from BCG. Clustering methods are introduced in [3], [4]. In these frameworks, feature vectors are first extracted from BCG segments, as the inputs of complete-link clustering [3] or k-means clustering [4], and then BCG segments are classified into heartbeat and non-heartbeat clusters. HR can be calculated from detected heartbeats. Multiple smoothed length transform (SLT) method is introduced in [5], which finds the heartbeats in BCG by first defining a search range for peak detection based on four fixed windows, then finding the heartbeat within the range. Dispersion-maximum method (DM) consisting of moving dispersion calculation method (MDC) and adaptive thresholding technique (ADT) is reported in [6] for calculating HR. MDC is used to highlight instantaneous amplitude vibration. J-peak is detected using ADT that determines the largest peak in a specific region. HR is calculated from the J-peaks in 1-min window. Above methods show a common weakness, i.e. they face difficulties in detecting heartbeats if the J-peaks of BCG signal are not obvious. As a result, HR calculated from the detected heartbeats differs from true value. Other methods [7], [8] for HR estimation from BCG make use of envelope extraction. Short-time energy and low-pass Butterworth filter are proposed to extract envelope of BCG [7], [8]. Heartbeats are recognised as the the largest peaks in envelope to calculate HR. Nevertheless, the usefulness of the envelope is highly associated with the quality of BCG signal, i.e. irregular patterns in BCG signal caused by motion artifacts result in poor envelope. Two promising methods in [9], [10] take advantage of template matching to detect heartbeats. Heartbeat template is extracted using unsupervised learning methods with a short duration of BCG signal. Subsequent heartbeats are determined by estimating the similarity between template and incoming BCG. Many empirical parameters are required in both methods. Therefore, the performance will be deteriorated without rational parameters on unknown signals.

In this paper, we present an algorithm that addresses the shortfalls in existing works, i.e. it requires no pre-setting parameters and overcomes the case with irregular pattern. The proposed method adopts Hilbert Transform (HT) to extract BCG envelope. Viterbi decoding (VD) algorithm is then used to estimate HR by finding the most likely state sequence from BCG recording.

The rest of this paper is organised as follows. Section II describes the dataset including system and experiment setup. The proposed methodology is presented in Section III. Experimental results are give in Section IV. Finally, conclusion is made in Section V.

II. Dataset

The system for data collection consists of one force sensitive sensor positioned under a chair's seat, signal conditioning circuitry, microcontrollers (MCU), Bluetooth as well as a mobile device. MCU receives the data from sensor and transits it to mobile device through Bluetooth.

We recruited 10 subjects, including 4 female and 6 male aged from 20 to 30 years old, to collect BCG recordings. During data acquisition phase, subjects were sit on the chair embedded with a sensor. During the data collection, subjects were to perform tasks such as talking, reading, and seating posture adjustment. ECG signal was recorded simultaneously with electrodes attached to the chest as well. It lasted approximately 17 minutes (min) for every subject.

III. Methodology

A. Overall Architecture

The proposed algorithm (HTVD) is composed of preprocessing, Hilbert Transform, and Viterbi decoding. Raw BCG is preprocessed to eliminate out-of-band frequency. Hilbert Transform is used to extract the fundamental frequency in the BCG signal, which represents the repetition of J-peaks. HR is estimated using Viterbi decoding which finds the best optimal path through time-frequency state-space plane, where the time-frequency spectrogram of the extracted envelope is seen as the emission probability matrix. The overall architecture is shown in Fig. 1. HR calculation is done by a 10 s window that slides through the BCG signal with an incremental step of 2 s.

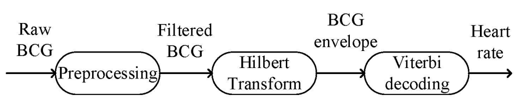

Fig. 1. The overall architecture of the proposed method.

B. Preprocessing

BCG is generated from the vibrations of heartbeat. Other motions, such as respiration, talking, and movements can easily contaminate BCG since the force sensor is highly sensitive to the vibrations. In addition, power line interference and muscle contraction are common interference sources that corrupt BCG signal.

The effective frequency of BCG lies in a low frequency band. A bandpass filter is thus employed to remove noises. The bandpass filter is selected as Butterworth with the 3-dB cutoff frequencies set to 0.7 Hz and 10 Hz, respectively. Therefore, respiration signal with typical frequency lower than 0.5 Hz is removed.

C. Hilbert Transform

It is less effective to get HR information directly from the Fourier transform in the case of BCG signal [11]. It is attributed from the phenomena that there is no outstanding fundamental frequency corresponding to HR in BCG signal. Consequently, Hilbert Transform is used to tackle this challenge which enhances the BCG envelope.

BCG data $s(t)$ can be modelled as (1) after removing respiratory signal.

$$s(t) = a(t)\cos(2\pi f_0 t) + e(t), \tag{1}$$

where $a(n)$ is the periodic heartbeat train modelling the repetition of J-peaks in BCG signal. The repetition frequency equals to heart rate. Indeed, $a(n)$ is invisible, only modulated $a(n)$ with frequency f_0 is observable. $e(n)$ is additive noise.

In order to extract heartbeat envelope from the modulated signal, we apply Hilbert Transform to achieve this target. Hilbert Transform merely produces 90 degree phase shift of the input signal. Thereby, we can combine original signal and output signal of HT to generate analytical signal ($h(t)$), given in (2).

$$h(t) = s(t) + js'(t), \tag{2}$$

where $s'(t)$ is imaginary part after the 90 degree phase shift of $s(t)$. When noise is negligible and the variation of heartbeat envelope is narrow compared to modulation frequency, $s'(t)$ approximately equals to (3).

$$s'(t) \approx a(n)\sin 2\pi f_0 t \tag{3}$$

The square amplitude of $a(n)$ is calculated by removing the unwanted modulation component, as (4).

$$m(t) = |h(t)|^2 = (s^2(t) + (s'(t))^2) = a^2(t). \tag{4}$$

Fig. 2 shows the performance of the proposed HT for HR estimation. It can be seen from Fig. 2 (b) that the spectrum by Fast Fourier Transfrom (FFT) of BCG signal has many peaks and the largest spectral amplitude differs much from true HR. It demonstrates that spectrum of BCG can not reflect HR information. The improvements using HT to measure HR is shown in Fig. 2 (c). Clearly, the spectrum of the envelope produces significant frequency corresponding to HR and its harmonics, and HR is acquired by finding the largest spectral amplitude.

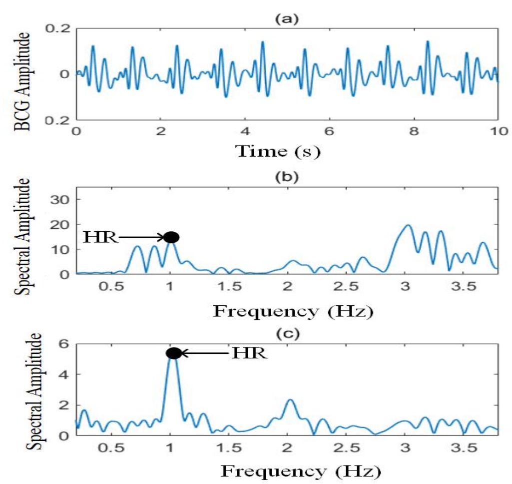

Fig. 2. An example of HT to estimate HR. (a) BCG signal. (b) Spectrum of the BCG . (c) Spectrum of the envelope.

D. Viterbi Decoding

It is able to acquire HR using HT method for clean BCG signal. However, HT is incapable of detecting HR if BCG signal is corrupted by noise, for instance, motion artifacts. As shown in Fig. 3, true HR being 63.17 beats per minute (BPM) is shifted from the largest spectral amplitude of envelope. The proposed method presents a novel solution to deal with this problem. It estimates HR in a probabilistic framework using Viterbi decoding.

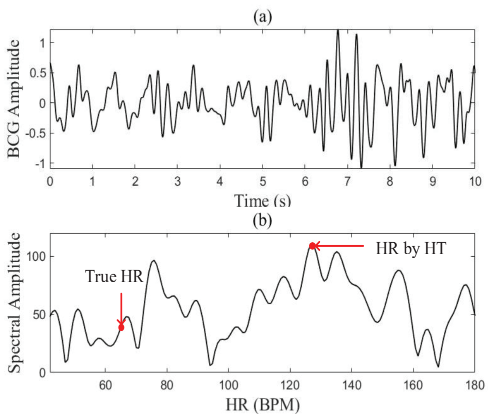

Fig. 3. An example of HT for Corrupted BCG. (a) Corrupted BCG signal. (b) Spectrum of the envelope.

The emission probability matrix E in VD algorithm is expressed as the spectral amplitude of BCG envelope. It represents the frequency with larger amplitude is more likely to be selected as HR. Zero-padding method is used in FFT to increase frequency resolution. The contents from 0.7 Hz to 3 Hz that correspond to the HR of 60 BPM to 180 BPM are kept. This is because it is enough range for person in a natural in-home environment. Therefore, the emission probability matrix is considered as a M-by-N state-space map. M denotes M states determined by the size of preserved FFT bins, and every bin represents one discrete HR value. N is the time windows, indicating observation number. The element in the i-th row and j-th column is denoted as E_{ij}, the value of which is the magnitude of the i-th FFT bin for the j-th time window. Transition probabilities matrix Q in VD with size of N-by-N indicates the likelihood of changing from one state to another state. Q_{ij}, i-th row and j-th column in Q, is the probability from i-th HR value to j-th HR value. It is estimated by counting the transitions among all states based on ground truth HR from ECG signal. In order to guarantee the testing recording not participate in the procedure of Q estimation, only ground truths of all other ECG recordings are used for Q estimation.

After transition and emission probability matrices are estimated, the VD algorithm is utilized to find the most probable path with the highest cumulative probability using transition and emission probability matrices through the time dimension, t :

$$V_1(i) = \pi_i E_{i1}, \qquad \text{where } (1 \leq i \leq M), \tag{5}$$

$$V_t(j) = \max_{1\leq i\leq N} [V_{t-1}(i) Q_{ij}] E_{jt}, \quad \text{where } (1 \leq j \leq M, 2 \leq t \leq N), \tag{6}$$

$$\Omega_t(j) = \arg\max_{1\leq i\leq N} (V_{t-1}(i) Q_{ij}), \text{where } (2 \leq t \leq N), \tag{7}$$

where π_i are prior probabilities. The probability of most likely sequence of states is recursively calculated according to (5), (6), (7). After that, the optimal state train is backtracked as (8), (9).

$$i_N = \arg\max_{1\leq i\leq N} [V_T(i)], \tag{8}$$

$$i_t = \Omega_{t+1}(i_{t+1}), \text{where } (t = N-1, N-2, \cdots, 1). \tag{9}$$

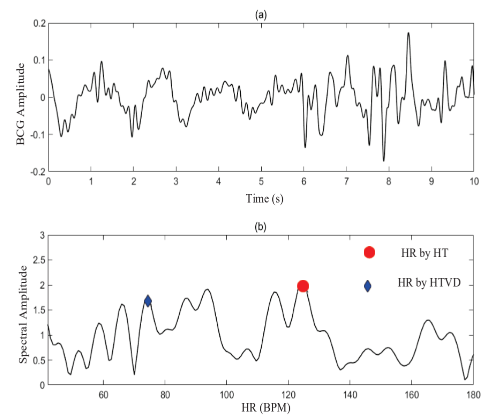

Fig. 4. An example to estimate HR by Viterbi decoding. (a) 10-s BCG signal. (b) HR refinement using VD.

The state sequence determined by VD algorithm is converted to HR estimates. Fig. 4 illustrates HTVD to estimate HR. The estimated HR of 123.40 BPM by HT is refined to 74.16 BPM using HTVD, with the true HR being 74.75 BPM.

IV. Experimental Results

A. Performance Metrics

ECG signal provides a reference of HR against estimated HR using the proposed method. R-peaks in ECG are detected by Pan-Tompkins algorithm [12], which are then manually checked to guarantee all R-peaks are correctly detected. Ground truth of HR is calculated as 60/T BPM with T representing mean R-R interval in time window.

Mean absolute error (MAE) and standard deviation of absolute error (STD) are adopted to assess the accuracy for HR estimation:

$$\text{MAE} = \frac{1}{N}\sum_{k=1}^{N} |\text{HR}_{\text{BCG}} - \text{HR}_{\text{ECG}}|, \tag{10}$$

$$\text{STD} = \sqrt{\frac{1}{N}\sum_{k=1}^{N} (|\text{HR}_{\text{BCG}} - \text{HR}_{\text{ECG}}| - \text{MAE})^2}, \tag{11}$$

TABLE I
MAE AND STD FOR HR ESTIMATION USING DIFFERENT METHODS

Subject	Time(Min)	SEN [7]		[8]		SLT [5]		HT		VD		HTVD(proposed)	
		MAE (BPM)	STD (BPM)	MAE (BPM)	STD (BPM)	MAE (BPM)	STD (BPM)	MAE (BPM)	STD (BPM)	MAE (BPM)	STD (BPM)	MAE (BPM)	STD (BPM)
1	19.20	0.85	1.44	0.64	0.85	1.57	3.00	0.48	0.39	1.73	1.90	0.45	0.35
2	18.94	6.34	6.40	10.89	8.72	14.35	12.84	15.62	26.18	6.24	7.78	1.72	2.80
3	12.96	4.45	4.76	15.85	12.52	9.42	11.04	5.26	9.78	13.93	7.50	3.00	3.98
4	14.70	2.09	4.80	3.51	5.77	1.33	2.95	2.88	10.24	3.16	3.86	0.97	1.42
5	15.57	2.21	4.12	6.83	7.62	3.03	3.57	1.20	4.70	12.09	8.82	0.72	0.74
6	19.18	3.68	5.44	7.21	13.07	7.73	9.26	7.90	19.66	2.03	1.91	1.10	1.40
7	15.59	3.06	5.68	8.04	11.76	2.73	5.51	2.45	6.78	2.32	3.57	1.78	4.32
8	18.16	1.83	3.10	1.54	3.08	1.15	2.14	1.23	3.71	1.45	1.39	1.06	1.37
9	15.83	5.80	5.96	7.54	9.39	5.65	7.30	6.51	13.36	12.21	11.58	1.37	1.75
10	14.87	2.29	3.56	4.78	6.83	2.07	4.61	2.53	7.27	2.70	4.68	1.39	1.81
Mean	16.50	3.26	4.53	6.68	7.96	4.90	6.22	4.61	10.21	5.79	5.30	1.36	1.99

where N is total number of time window, HR_{BCG} and HR_{ECG} are HR calculated from BCG and ECG, respectively.

B. Performance Assessment

Table I summaries MAE and STD using the proposed method. On the dataset of 10 recordings, HTVD achieves MAE of 1.36 BPM and STD of 1.99 BPM. For comparison, SEN, SLT and the method in [8] are implemented, MAEs and STDs of which are listed in Table I as well. It can be seen that the proposed method outperforms other methods on the dataset in terms of MAE and STD. SLT [5] selects window sizes experimentally, which increases the risk of poor generalization on the unknown data. The works in [7], [8] extracts energy envelope of BCG signal using short-time energy function and low-pass filter, respectively. The envelope appears irregular when BCG does not have consistent pattern. Thereby, accuracy degrades for recording 2, 3, 9 due to poor BCG signals caused motion artifacts and talking. The performance using HT by searching the largest spectral amplitude is also listed in Table I. It shows HR can be well estimated for good quality BCG, such as recording 1. However, HT still can not deal with poor BCG owing to noises. Table I also gives accuracy just using VD without HT, the MAE of which degrades from 1.36 BPM to 5.79 BPM. This result indicates that spectrum of BCG by FFT can not reflect HR information, which complies with the analysis described in Section III C. It also verifies that it is essential to extract envelope by HT. The proposed HTVD shows much better results especially for BCG signals corrupted by various types of noises, demonstrating its ability to be used in home environment. Fig. 5 shows regression plot with respect to HR estimation, where Pearson correlation coefficient (r) is 0.94. It is worth noting that HTVD is fully automatic and parameter-free probabilistic manner using data-mining method.

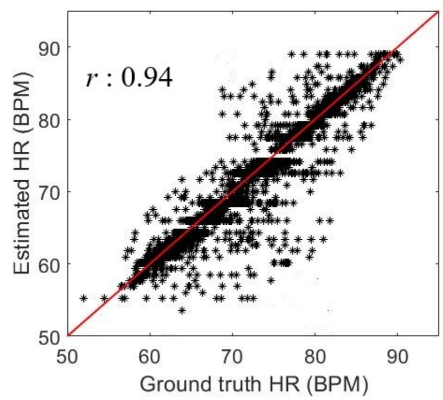

Fig. 5. Estimated HR versus ground truth HR

V. CONCLUSION

This paper presents an obstructive system for heart rate estimation with threshold-free method. It is shown that Hilbert Transform can extract envelope with a significant frequency corresponding to heart rate for normal BCG signal. Viterbi algorithm is able to tackle the case with abnormal heartbeat caused by slight motion artifacts and talking. The proposed method requires no parameter to tune.

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