Towards precise tracking of electric-mechanical cardiac time intervals through joint ECG and BCG sensing and signal processing

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Abstract— **Automatic tracking of intra-beat cardiac activities in ballistocardiogram (BCG) is a highly interesting yet technically challenging topic for cardiac monitoring, due to the signal's high susceptibility to various forms of distortions. In this paper, we aim to further investigate the BCG waveform detection from a signal processing and analysis viewpoint. We collect synchronized electrocardiography(ECG) and BCG recordings from four healthy human subjects using an in-house built multi-physiological monitoring device. Particularly, we study post-exercise ECG-BCG signals that embed considerable variation in the heart beat during the post-exercise recovery phase. Furthermore, we develop an efficient and interactive tool for detecting and marking ECG-BCG waveforms in each heart beat. Through analyzing the detected time interval signals, we explore new interesting patterns of dynamic associations between different time interval signals. At the same time, we call for development of improved detection algorithms to address robustness and accuracy issues.**

I. INTRODUCTION

Recent years have seen an active research field of unobtrusive cardiovascular monitoring especially using new generation of ballistocardiogram (BCG) sensors [1]. BCG essentially detects the minuscule motion of the human body in response to the recoil forces of the cardiac ejection into the vascular system. Therefore, it carries critical information of mechanical signatures of cardiovascular activities, and can also be accessed unobtrusively, making it an important option for clinical toolbox as well as ubiquitous healthcare in homes, workplaces or even in microgravity environment[2].

A major research topic in the engineering field is related to estimating heart rate. Usually, the heart rate is estimated over a given time-windowed BCG waveform, where either time-domain features [3] or spectrum-domain features [4] are used to derive an estimate of average heart rate. Our earlier work [5] on multi-sensor fusion and cepstrum domain signal processing has also suggested that this approach can deliver more robust heart rate estimation in distorted BCG waveforms by various artifacts.

Beyond heart rate estimation, researchers have looked into measuring individual beat-to-beat intervals in BCG. In [6], the authors presented a parametric BCG waveform model and an algorithm for the detection of individual heart beats and beat-to-beat interval lengths, and tested the method on a bed-mounted force-sensor based BCG system. Importantly, it is shown that the method is able to accurately track the instantaneous heart rate, and this suggests the potential of BCG for heart rate variability (HRV) (see [7] for an independent BCG for HRV measurement) and irregular arrhythmia detection, which are more clinically relevant than average heart rate measurement.

Moving forward, it is interesting to investigate if BCG can provide accurate information about intra-beat cardiac activities that, for example, may correlate even better than electrocardiograph (ECG) with physiologically and anatomically significant ischemic coronary artery disease (see an example in [8]). A comprehensive overview of this inter-beat level of cardiac monitoring is beyond the scope of this paper. Instead, we would like to emphasize the timing intervals between BCG components or across to other cardiac signals: cardiac timing measurements are clinically important [9], and a number of studies have demonstrated the feasibility of measuring the time interval between ECG R-peak to the BCG J-peak, or between BCG I and J peaks [10].

However, it is a considerable challenge to automatically and accurately measure the time intervals, because the BCG waveforms are prone to distortions by various sources of artifacts such as body motions [10]. In other words, the key waveform components may not be well-defined in individual heart beats, often leading to detection errors in the algorithms .

In this paper, we aim to further investigate the automatic waveform detection and timing measurement in BCG, from a signal processing and analysis viewpoint. We collect synchronized ECG and BCG recordings from four healthy human subjects using an in-house built multi-physiological monitoring device. Different from prior arts such as [10], we study the post-excercise ECG-BCG signals that embed considerable variations in the cardiac functions. Furthermore, we develop an interactive semi-automatic tool for detecting and marking ECG-BCG waveforms in each heart beat. We analyze the measured and post-processed time interval signals and show that there are interesting patterns of dynamic associations between different time interval signals. We also discuss on the development of improved detection algorithms to address robustness and accuracy issues.

II. DATA COLLECTION

We built a sensing platform using the following components for the acquisition of BCG and ECG signals. Two fiber-optic based BCG sensor mats (see [11]) were attached to an arm-chair: one at the seat position, the other at the back

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position. Note that in the present study we investigate the sensor signal from the seat position only. A pair of disposable ECG electrodes were placed on the human's RA and LL points to capture a single lead ECG waveform. The BCG sensors' output and the ECG electrodes were connected to a Neuroscan's NuAmps neurophysiological signal amplifier running at 5KHz sampling rate and 22-bit ADC resolution. The digitized signals were monitored online while being saved to local storage using the Neuroscan's SCAN software.

In this preliminary study, we recruited five healthy adult volunteering subjects (all male). Ethical approval had been obtained from the National University of Singapore Institutional Review Board (NUS-IRB). None of the subjects had existing or recent history of cardiac conditions. With the aid of the experimenter, each of the subjects completed a predefined series of tasks: 5 minutes rest in the chair, 3 minutes cardio workout of running on a thread-mill at moderate intensity, 5 minutes post-exercise rest immediately after the workout. In both Task 1 and Task 3, the subjects were instructed to remain still and to avoid any body motion and posture change.

It is also particularly important to control the transfer time from the workout Task 2 to the post-workout rest Task 3, since the cardiac condition post-exercise could progress rapidly. Therefore, re-seating the subject, reconnecting the electrodes and sensors and stabilizing the signals must be practiced and optimized beforehand. In one of the subjects, this transfer was not done properly, rendering the recorded signal not capturing the critical change during the post-excercise recovery. Hence that subject was dropped from the data processing and analysis.

III. DATA PROCESSING WITH AN INTERACTIVE SIGNAL DETECTION AND MARKING TOOL

A. Preprocessing

All the recorded ECG and BCG signals were first down-sampled to 1KHz and notch-filtered to remove the 50-Hz powerline interference.

ECG signal was then high-pass filter processed using a 3rd order Chebyshev Type II digital filter at 1Hz stop-frequency and 30-db stop-band ripple, in order to remove low-frequency baseline fluctuation.

BCG signal was high-pass filter processed using a 3rd order Chebyshev Type II digital filter at 0.5Hz stop-frequency and 30-db stop-band ripple, so as to remove the respiratory component as well as other possible very low-frequency distortions. The signal was then low-pass filtered at 20-Hz using another 3rd order Chebyshev Type II digital filter with 30-db stop-band ripper.

B. The component detection algorithm

ECG signal processing involves detection of primarily the R peak, using a traditional time-domain signal processing algorithm. With the detected R peaks, the T peaks was then detected using a simple local maximum search in a specified time window with reference to the R peak. In one of the subjects, the T peak component was particularly strong
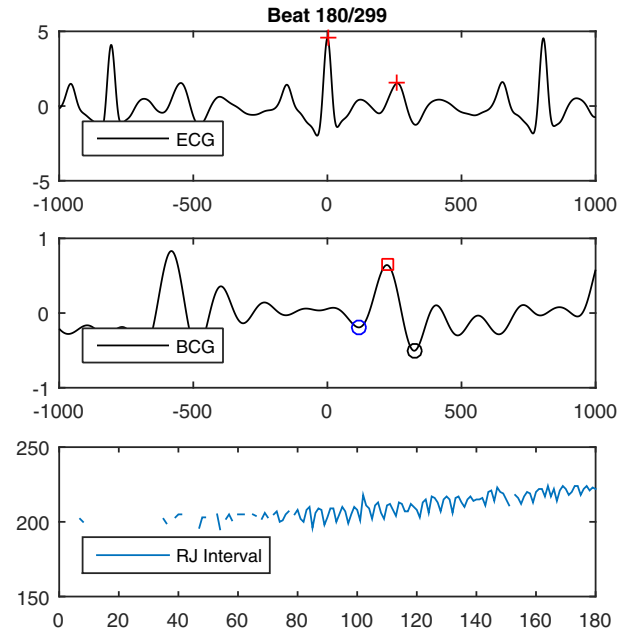

Fig. 1. A snapshot of the Interactive Detection and Marking Tool. In the upper two graphs, the X-axis indicates the time points in milliseconds with respect to the detected R peak of the present heart beat (the Y-axis value is normalized). In the bottom graph, the X-axis is the number of heart beat, while the Y-axis denotes the measured R-J interval in milliseconds. The tool receives mouse click events or keyboard events to mark (accept or reject) the measurement in this heart beat. Rejected heart beat points are excluded from the R-J interval plot in the bottom graph.

so that a specifically designed high-pass filter (i.e. T wave suppressing filter) was applied to the whole ECG signal just in order to facilitate the R-peak detection.

BCG detection was performed after detection of ECG R peaks. Particularly, the interactive tool (see next subsection) shows the concurrent ECG and BCG waveforms for a few heart beat cases of a subject, and the operator can then specify a time range of possible I-J-K waveforms on the plotted signals. This time range was applied uniformly to all the heart beats from this particular subject, and a local maximum search then detected the J-peak in the time range. Thereafter the I or the K peak was detected using local minimum search in the sub-time-window either before or after the detected J-peak.

C. The interactive marking tool

As mentioned earlier, BCG signal is extremely susceptible to various motion artifacts, making it crucial to validate the I-J-K detection in each heart beat. As far as we know, there is unfortunately neither established nor extensively validated and widely accepted automated algorithm available for the validation task. Thus, we develop a semi-automated interactive marking tool, which will still be useful in future studies for validating fully automated BCG peak detection methods.

The tool has built-in the component detection algorithm described in the previous subsection. It displays three graphs:

Subject	1	2	3	4
Number of heart beat	298	421	862	399
Number of rejection	11	8	250	45
Rejection Rate (%)	3.7	1.9	29.0	11.3

the upper graph plots the ECG heart beats and the markers of the detected R and T peaks; the middle graph plots the BCG heart beat and the markers of the detected I, J and K peaks: the lower graph plots the sequence of R-J interval measurement in every heart beat that have been validated.

The tool automatically iterates from the first heart beat till the last one. For the convenience of the operator (human expert), a positive validation (i.e. accept) can be performed either using the left-button on the computer mouse or the Enter button on the keyboard, a negative validation (i.e. reject) can be performed using the right-button on the computer mouse. The operator shall look closely at the morphology as well as the timing of the I-J-K complex in BCG. Since ECG signal is also subject to distortions, the operator shall also check the detection of R and T peaks in ECG. The R-J interval measurement sequence only plots the heart beat points with validated detection in both BCG and ECG.

Further details of the marking tool are omitted due to lack of page space, but will be presented in our separate manuscript in the future.

IV. RESULTS

Table I summarizes the statistics of validation outcome by using the interactive detection and marking tool. The range of rejection is quite large, from 1.9% to close to 30%. This indicates the present automated waveform detection algorithm described above may not be able to consistently produce accurate detection, to a large extend due to the fact that many affected heart beat waveforms were so corrupted that peak-detection based methodology became entirely suitable.

The heart rate was computed using the detected R peaks. Particularly, instantaneous R-R intervals (a.k.a beat-to-beat interval) were computed and the series of the intervals was smoothed using a moving average window at a length of 10 (heart-beats). This essentially produced an average heart rate estimate in 10 heart beat time window. The result is illustrated in Figure 2.

In three of the four subjects, there was a clear trend of decreasing heart rate, which was what was expected in the recovery phase of the experiment protocol. Due to the complexity and variation of the physiologic stress level in the cardio workout, and also because of the variation in the transfer timing from workout to recovery, it is difficult to directly compare the recovery rate among the subjects. Nevertheless, it appears that it takes no less than 100 heart beat to recover to a relative stable state after our moderate cardio workout task.

The third subject, however, is an exceptional case, in which the heart rate stayed at the a low yet consistent level.
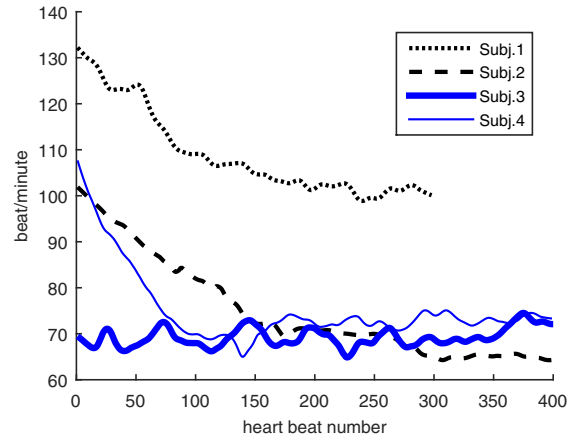

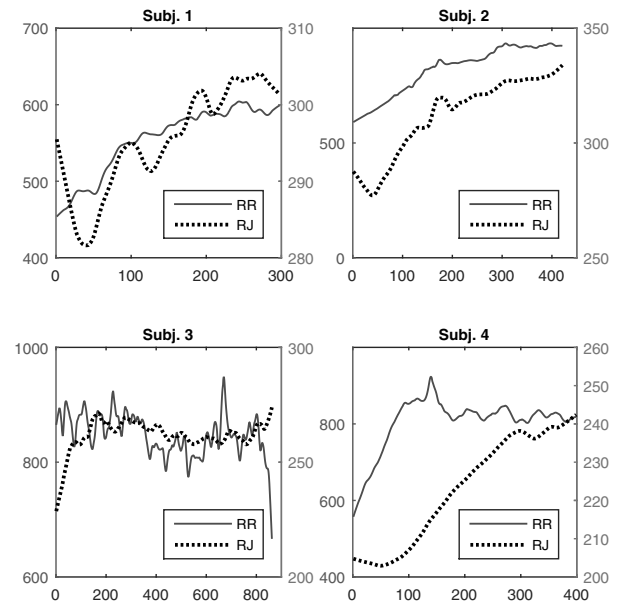Fig. 2. Progresses of recovery heart rate post cardio workout.

Fig. 3. Associations of RR and RJ intervals. Each graph represents a particular subject. Both of the left ('RR') and right ('RJ') Y-axes are in milliseconds. The X-axis is the number of heart beat.

There are a few plausible reasons: the subject did not receive sufficient workload during the treadmill running task; he was very fit and had a very quick recovery; his transfer from the cardio workout to the BCG+ECG measurement station, however, was impeded by a technical hiccup.

Interestingly, although the inter-beat interval (IBI) did not capture his recovery, our BCG and ECG timing measurement captured the recovery process, as will be shown in below.

Figure 3 illustrates the processes of R-R and R-J intervals in each of the four subjects. There were similar trends in both processes, in terms of longer intervals. As expected, the growing intervals indicate the decreasing cardio workload (heart rate) and cardiac contractility (R-J interval). But the two processes were not synchronized. In Subjects 1, 2 and
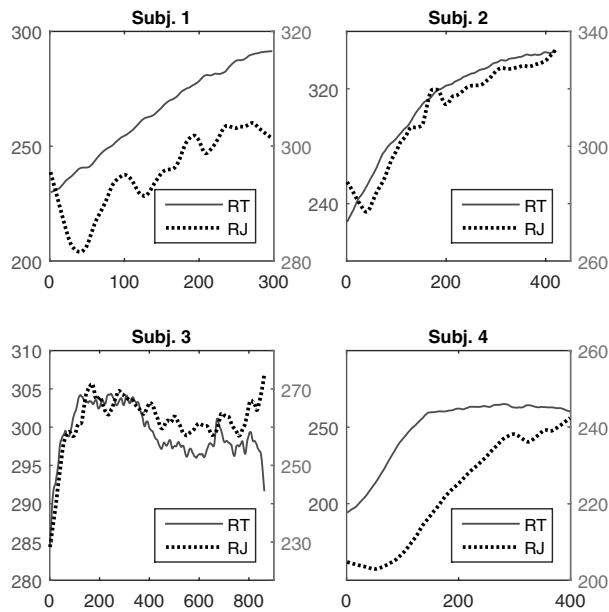
Fig. 4. Associations of RT and RJ intervals. Each graph represents a particular subject. Both of the left ('RT') and right ('RJ') Y-axes are in milliseconds. The X-axis is the number of heart beat.

3, the R-J interval process exhibited a dip in the early stage post-workout. In Subject 4, the R-J recovery still kept going well after the RR interval recovered until 200 heart beat later.

Figure 4 illustrates the time courses of the measured R-T and R-J intervals in each of the four subjects. Similarly to the previous R-R and R-J comparison, the early downward turn in the R-J interval process (in all except Subject 3) was not correlated with the consistent ascending trend in the R-T interval process. On the other hand, compared with the previous figure, there is a closer relationship between R-J and the ECG-derived timing in Subject 3, where both processes captured the recovery progress. This suggests that the R-T recovery process may be longer than R-R recovery process: Subject 4 actually validates this where the R-T asymptotically moved to the stable range at around 150 heart beat, while R-R achieved at around 100 heart beat. Nevertheless, it seems that the R-J interval is able to capture an even longer process of recovery.

V. CONCLUSIONS

In this paper, we have investigated the BCG waveform detection from a signal processing and analysis viewpoint. We collected synchronized ECG and BCG recordings from four healthy human subjects using an in-house built multi-physiological monitoring device. We study the post-cardio-workout ECG-BCG signals that embed considerable variations in the cardiac functions. Furthermore, we develop an interactive semi-automatic tool for detecting and marking ECG-BCG waveforms in each heart beat. We analyze the measured and post-processed time interval signals and show that there are interesting patterns of dynamic associations

between different time interval signals. Specifically, all the R-R, R-T and R-J intervals can capture the post-workout recovery cardio process, but R-J interval has a longer process of recovery, and also exhibits an interesting initial downward turn that may be the subject of other physiologic and clinical studies in the future.

Furthermore, the result also indicates that accurate detection of BCG waveform in each individual beat is a challenging task, subject to considerable distorations by various motion artifacts in the same spectrum range of BCG. Thus, we suggest that furture work shall look into development and extensive validation of advanced signal processing techniques based on more principled modeling of beat-to-beat dynamics of cardiac timing and waveform morphology.

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