ROBUST BEAT-TO-BEAT DETECTION ALGORITHM FOR PULSE RATE VARIABILITY ANALYSIS FROM WRIST PHOTOPLETHYSMOGRAPHY SIGNALS

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ABSTRACT

Heart rate variability (HRV) from electrocardiograms (ECG) is a well-known diagnostic method for the assessment of autonomic nervous function of the heart. A more convenient approach to assess cardiac function is by using Photoplethysmography (PPG) waveforms where pulse rate variability (PRV) replaces HRV. However, the unavailability of robust detection algorithms for PPG signals has prevented the medical market from providing clinical diagnosis using PRV and from measuring biological information for wellness purposes, such as sleep stage, stress state, and fatigue.

This paper provides a robust peak and onset detection algorithm for beat-to-beat (B2B) pulse interval analysis using PPG signals. We demonstrate our method through large data collection with the Analog Devices (ADI) multi-sensory watch platform with high coverage, sensitivity, and low Root Mean Square of Successive Difference (RMSSD) as compared to the B2B results from ECG signals.

***Index Terms*—** Heart Rate Variability, Photoplethysmography (PPG), Pulse Rate Variability (PRV), Beat-to-Beat, Delineation.

1. INTRODUCTION

Heart Rate (HR) monitoring is a key feature in many existing wearable and clinical devices but a function to measure the continuous heart rate variability (HRV) using beat-to-beat (B2B) pulse interval has not yet been provided with these devices. HRV consists of changes in the time intervals between consecutive heartbeats called interbeat intervals extracted from electrocardiogram (ECG) [1]. HRV contains well known biometric information reflecting the sympathetic and parasympathetic activities of the autonomic nervous system [2]. Researchers have widely used HRV as a tool to support clinical diagnosis and measure biological information for wellness purposes, such as sleep stage, stress state, and fatigue [2, 3]. Given the technical requirements of ECG measurements, the signal may not always be available in accident/catastrophe sites, battlefields, or areas where ECG can cause electrical interference [4].

Pulse rate variability (PRV) extracted from Photoplethysmography (PPG) signals could be used as an alternative to HRV [5–7]. The PPG signals are obtained by illuminating human skin using an LED and by measuring the intensity changes due to blood flow in the reflected light by a photodiode. Furthermore, PPG can provide relevant information about the cardiovascular system, such as heart rate, arterial pressure, stiffness index, pulse transit time, pulse wave velocity, cardiac output, arterial compliance, peripheral resistance, and others [8–10]. However, the performance of PPG-based algorithms can be degraded by poor blood perfusion, ambient light, and most importantly, motion artifacts (MA) [11]. Many signal processing techniques have been proposed to remove the MA noise including the Analog Devices Inc. (ADI) motion rejection and frequency tracking algorithm by using a three-axis acceleration sensor placed close to the PPG sensor.

It is important to extract significant points such as systolic peaks, onsets, and dicrotic notches from PPG waveforms accurately for PRV analysis [12]. The onset of the PPG waveform is due to the commencement of blood expulsion from the heart to the aorta, while the dicrotic notch is the end of blood ejection or the closure of the aortic valve. The unavailability of robust detection algorithms for PPG signals has, at least partially, prevented researchers from fully conducting PRV analysis using PPG. Some previous work on PRV ignores the fiducial points [13], some reported using manual or empirical detection of the systolic peaks [14], and some are based on non-validated time window-based algorithms to obtain the pulse peak [15].

This paper proposes a robust peak and onset detection algorithm which uses a delineation method originally proposed for Arterial Blood Pressure (ABP) waveforms [16]. It is important to note that PPG signals using wirst-worn wearable devices contain many motion artifacts, baseline fluctuations, reflected waves and other noise that can affect the behaviour of detection algorithms [6]. Therefore, the data is pre-processed first before feeding it to the B2B extraction model. The automatic delineator used in this work is a hybrid approach in which different pre-processed signals from raw PPG and the first derivative of the signals are used to extract both the peaks and onsets. We use a large database collected using our ADI watch platform that provides synchronized PPG and ECG signals. In terms of memory footprint, this algorithm is light and can be used as an embedded algorithm in the ADI watch platform. The algorithm is validated and compared with the B2B results from ECG signals using coverage, sensitivity, positive productivity and Root Mean Square of Successive Difference (RMSSD) [17].

The paper is organized as follows. Section 2 defines the B2B algorithm components and provides a block diagram of the approach. In Section 3, the results from applying the proposed algorithm on the PPG signals collected from the ADI platform are compared to ECG B2B results. Finally, section 4 concludes the paper.

2. BEAT-TO-BEAT ALGORITHM BASED ON THE PPG MORPHOLOGY

In this section, we explain the details of the proposed B2B algorithm for wrist PPG signals comprised of (i) pre-processing, and (ii) high resolution B2B extraction modules. A block diagram of the algorithm is shown in Fig. 1.

2.1. Pre-processing

The susceptibility of the PPG signal to poor blood perfusion of the peripheral tissues and motion artifact is well known [18]. In order to minimize the influence of these factors in the subsequent phases

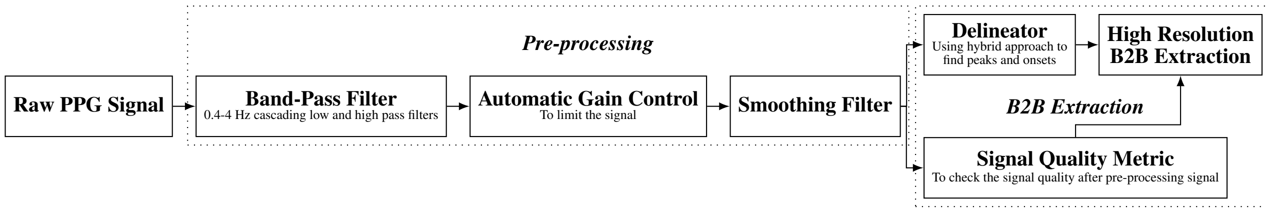


Fig. 1: Flowchart of the proposed B2B extraction algorithm comprised of (i) pre-processing and (ii) high resolution B2B extraction.

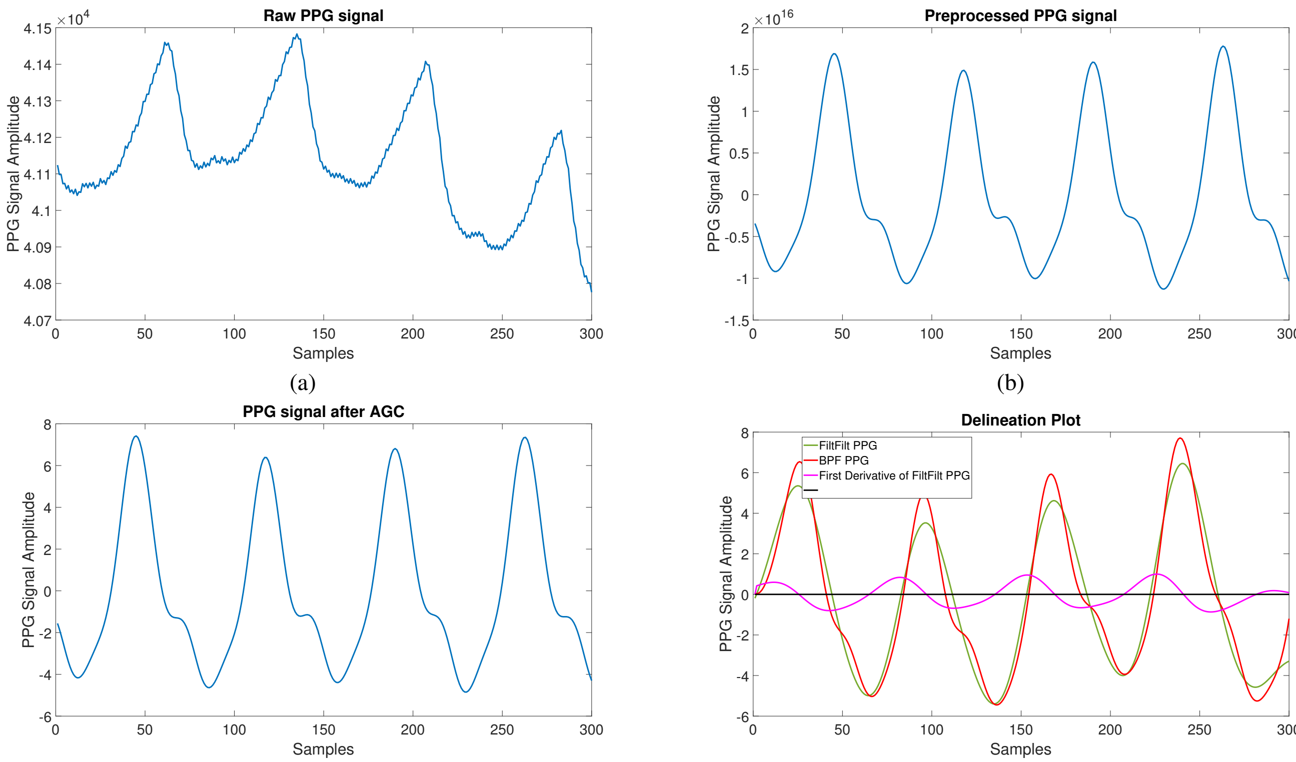


Fig. 2: PPG plots: (a) Raw signal, (b) after filtering, (c) after filtering and AGC, and (d) the delineation plot.

of the PPG analysis for B2B estimation, a pre-processing stage is required. This step is comprised of:

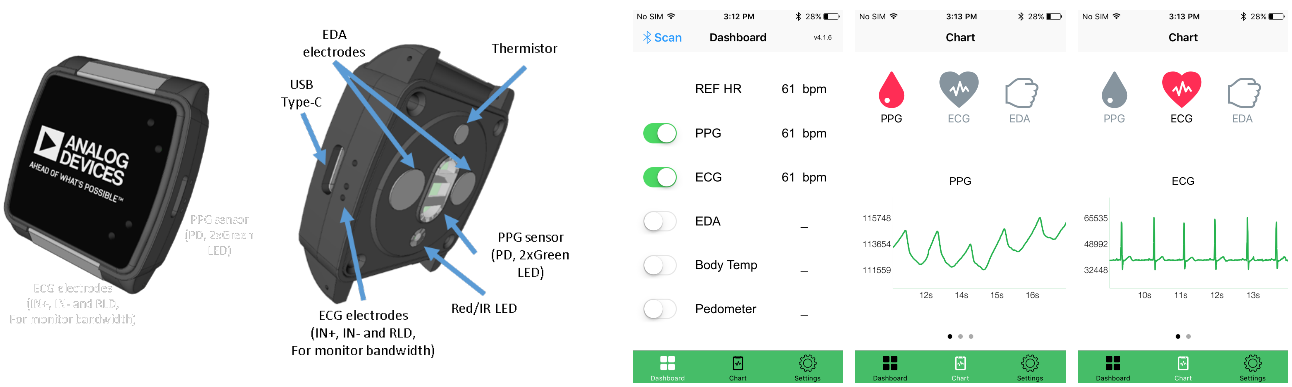
1. Framing and windowing
2. Bandpass filtering (0.4Hz-4Hz)
3. Automatic Gain Control (AGC) to limit the signal level
4. Signal smoothing and baseline wandering removal

The PPG input data is processed using a window of T_0 seconds and further blocks are processed by moving the window with mT_0 (i.e., $m = 3/4$) overlap. A bandpass filter is then required to remove both high frequency components (such as power sources) of the PPG signals as well as low frequency components such as changes in capillary density and venous blood volume, temperature variations, and so on. Fig. 2 (a-b) shows a PPG signal before and after filtering. The filter has a cut off frequency at 0.4 and 4 Hz. The fundamental frequency of the HR ranges between 0.4 to 3 Hz. Therefore, using a range that is a little higher for B2B estimation allows us to include harmonics that emphasize the beat times. Sudden spikes are removed from the filtered signals using a median filter. Then, an AGC module limits the signal level to $\pm V$ volts in order to verify the selected peaks by checking the amplitude of the signal at a later stage. The durable PPG measuring process for HRV unavoidably introduces another type of artifact, such as baseline wandering. Consequently, a low pass Finite Impulse Response (FIR) filter is used to smooth the array of the PPG samples in the frame (shown in Fig. 2 (c)), to remove the baseline wandering noise, and to get a smoother signal for the delineation module.

2.2. High resolution B2B extraction module

The B2B extraction algorithm consists of the following modules:

1. Interpolation
2. Delineation
3. High resolution B2B extraction



(a) (b)

Fig. 3: ADI platform and tool: (a) ADI watch Gen 2 data collection platform , and (b) ADI mobile iOS app interface (Dashboard, PPG, ECG)

4. Signal quality metric

The output of the pre-processing module is fed to an interpolation block to increase the accuracy of the B2B extraction algorithm. If a PPG segment from t_0 to t_T is given in the first frame with B2B interval of b_0 and b_T, we linearly interpolate the B2B interval values using n points between the endpoints and then extract a high resolution B2B (e.g, 1 msec resolution) from b_0 and b_T. Next, the delineation module relies on both the signal morphology as well as rhythmic information to extract the peaks and onsets. Therefore, not only are the systolic peaks needed, but also the onsets and dicrotic notches should be reported for B2B detection. The proposed delineator is theoretically similar to [12, 16] which is adapted to the wrist PPG signals by using a pair of inflection and zero-crossing points from the first derivative of the signal. Fig. 2 (d) plots both inflection and zero-crossing points for PPG characterization. For the zero-crossing points, the signal is processed with a zero phase distortion filter which minimizes start-up and ending transients by matching initial conditions. This is to make sure that the time-domain features are preserved after filtering. Note that the onsets from the derivative of the PPG waveform correspond to zero-crossing points before a maximal inflection, while the systolic peak relates to zero-crossings after that inflection point. The signal quality metric used for this B2B algorithm is *clarity* and indicates the extent that a signal has a tone. This metric was originally proposed in [19], where a normalized squared difference function (a form of auto-correlation function) is used for finding the periodicity of the signal. We use this metric to decide when the B2B algorithm is confident to report the peaks and onsets.

3. EVALUATION RESULTS FROM ADI WRIST PLATFORM

Our PPG B2B algorithm results are compared to results from the Pan Tompkin's algorithm [20] which is a well recognized algorithm for ECG peak detection. Data was collected to evaluate our algorithm using the ADI Vital Signs Monitoring (VSM) wrist watch platform. The ADI VSM iOS application was used to interface with the watch over a bluetooth connection. The ADI wrist watch includes a PPG sensor used to collect PPG signal from the subject's wrist. The ECG signal was also collected on the ADI wrist watch. Three ECG electrodes were attached to the subject's chest area. Wires from these electrodes were connected to the ADI wrist watch where the signals were processed and logged concurrently with the PPG signal. This platform provides synchronized PPG and ECG signals. Fig. 3(a) shows the ADI wrist watch used for data collection while Fig. 3(b) shows the iOS app interface and sample signals obtained from the platform.

3.1. Evaluation Metrics and Results

Before computing the beat to beat metrics, it is important to have an outlier removal process that identifies missing/extra peaks in the Pan Tompkin's algorithm outputs and our PPG beat-to-beat algorithm outputs. Ignoring missing/extra peaks causes abnormal beat durations that would lead to inaccurate results. Missing/extra peaks in the ECG signal were identified by looking at the successive beat durations provided by the pan tompkin's algorithm. Any ECG peak that changed the beat duration more than 20% was labelled an outlier. After removing these ECG peaks, missing/extra peaks in the PPG signal were identified by correlating each ECG peak with a peak in the PPG signal. A PPG peak was correlated with an ECG peak if it is within time proximity of the ECG peak. When a PPG peak cannot be identified or too many peaks are identified within the time proximity of an ECG peak, these were identified as outliers. The abnormal beat durations that these missing/extra PPG beats would cause are ignored as outliers during metrics calculations.

A number of metrics are computed using the beat-to-beat values from our proposed algorithm and from the Pan Tompkin's algorithm. These metrics are: (i) Coverage (Eq. (1a)); (ii) Sensitivity or Se (Eq. (1b)); (iii) Positive Predictivity or P$^+$ (Eq. (1c)); and (iv) Root Mean Square of Successive Differences or RMSSD (Eq. (1d)). Fig. 4 presents a visual representation of some of the values used for the metrics calculations.

$$\text{Coverage} = \frac{\#\text{Identified PPG Peaks}}{\#\text{Identified ECG Peaks}} \tag{1a}$$

$$\text{Se} = \frac{\text{TP}}{\text{(TP+FN)}} \tag{1b}$$

$$\text{P}^+ = \frac{\text{TP}}{\text{(TP+FP)}} \tag{1c}$$

$$\text{RMSSD} = \sqrt{\frac{1}{N}\sum{}_{i=1}^{N}(|\text{IBI}_{i-1} - \text{IBI}_i|^2)}, \tag{1d}$$

where *TP (true positive)* is the number of heart beats correctly identified by the PPG B2B algorithm, *FP (false positive)* is the number of PPG heart beats that did not correspond to an actual heart beat in the ECG, and *FN (false negative)* is the number of heart beats that

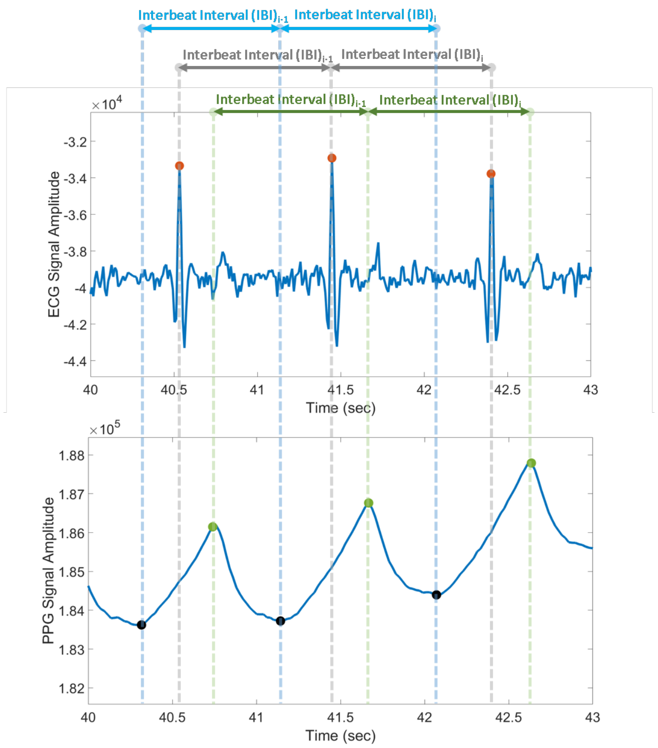


Fig. 4: ECG and PPG signals with IBIs shown and the respective peaks and onsets from the B2B algorithm on the raw PPG signals.

the PPG B2B algorithm missed. The *Interbeat Interval (IBI)* is the time between successive ECG peaks, PPG peaks, or PPG onsets.

In order to evaluate our algorithm, PPG and ECG signals are collected simultaneously for each subject. Data was collected on a large number of subjects of different ages, skin tones, and body types. This was to ensure that our evaluation results would be relevant across all populations. Data is collected on 27 subjects (male and female with different skin tones) each for 2 minutes and 30 seconds. Subjects were asked to stand for the first half and sit for the second half of the time. Table 1 presents the average results of each of the metrics for the beat to beat algorithm. As shown in the table, the coverage, sensitivity, and positive predictivity are all above 83% with the average RMSSD difference below 20 msec for the wrist data as compared to the results from the ECG signals.

Metric	Result
Coverage	83%
Sensitivity	87%
Positive Predictivity	98%
Average PPG vs ECG RMSSD Difference	12msec

Table 1: Beat-to-Beat metrics results.

4. DISCUSSION AND CONCLUSION

A robust peak and onset detection algorithm for PRV analysis from wrist PPG signals was proposed in this work. The algorithm used multiple stages of pre-processing and suggested a hybrid delineation algorithm to detect the fiducial points of wrist PPG signals. The ADI multi-sensory watch was used as our evaluation platform to test the proposed algorithm. The results showed strong correlations and concordance with respect to the ECG HRV. Future work will focus on applying motion rejection algorithms and on dealing with the missing beats issue in the PRV analysis.

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