Smartwatch PPG Peak Detection Method for Sinus Rhythm and Cardiac Arrhythmia

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Abstract— **The aim of our work herein was to design a photoplethysmographic (PPG) peak detection algorithm which automatically detect and discriminate various cardiac rhythms—normal sinus rhythms (NSR), premature atrial contraction (PAC), premature ventricle contraction (PVC), and atrial fibrillation (AF)—for PPG signals collected on smartwatch. Compared with peak detection algorithm designed for NSR, the novelty is that our proposed peak detection algorithm can accurately estimate heart rates (HR) among various arrhythmias, which enhances the accuracy of AF screening. Our peak detection method is composed of a sequential series of algorithms that are combined to discriminate various arrhythmias, as described above. Moreover, a novel Poincaré plot scheme is used to discriminate AF with Rapid Ventricular Response (RVR) from normal basal heart rate AF. Moreover, the method is also able to differentiate PAC/PVC from NSR and AF. Our results show that the proposed peak detection algorithm provides significantly lower average beat-to-beat estimation error (> 40% lower) and mean heart rate estimation error (> 50% lower) when compared to a traditional peak detection algorithm that is known to be accurate for NSR. Our new approach allows more accurate HR estimation as it can account for various arrhythmias which previous PPG peak detection algorithms were designed solely for NSR.**

I. Introduction

Several recently published studies have already demonstrated that electrocardiogram (ECG) data from a smartwatch band can be used to detect atrial fibrillation (AF) [1], [2]. The use of an ECG band for AF detection in its present form, which requires the user to touch a metal sensor on the wrist band with their non-watch hand, is not the optimal approach for detection of paroxysmal AF. This user-invoked measurement could too easily miss minimally symptomatic and brief paroxysms of AF. However, photoplethysmogram (PPG) recorded on a smartwatch could provide an ideal way for passive screening of paroxysmal AF since it can be programmed to continuously collect the data.

Wearable devices such as smartwatches enable near-continuous PPG data collection and show great promise for AF screening and monitoring[3]. AF detection via these smart devices offers the potential for early diagnosis, but adoption of the technology by both clinicians and patients requires that these devices are easy to use, accurate, and provide clinically meaningful results in a manner that respects the workflow of clinicians. Nonetheless, peak detection algorithms designed from normal subjects are not optimized on cardiac arrhythmia data [1], [2], even if these algorithms may be adequate for AF detection.

Peak Detection algorithms for PPG signals has been well validated from clean signal collected on normal sinus rhythm (NSR) subjects [4]. However, when peak detection confronts various forms of AF including rapid ventricular responses, motion and noise artifacts which are common in PPG data from wrist-based wearable devices, can all be major causes of false positive detection of AF since motion artifacts can mimic AF characteristics [1], [2].

To date, the published works on peak detection for PPG pulsatile recordings has been largely devoted to the traditional fingertip pulse oximeters often found in clinical settings [5]. One of the most accurate PPG peak detection algorithms was proposed by Lu et al.: an Empirical Mode Decomposition (EMD)-based local minima detection method [5]. However, it cannot be used to automatically detect accurate heart rates for AF. Another method proposed by Shin et al. [6] uses an adaptive threshold method to detect maxima of PPG pulses. However, adaptive threshold method cannot separate merged PPG peaks when both the incident and reflected waves of PPG merged for fast basal heart rate (HR) (e.g. > 140 beats/min) AF, premature atrial contraction (PAC) or premature ventricular contraction (PVC). This is because blood ejected by irregular heart contraction causes the amplitude and velocity of PPG waveform changing rapidly and is one of the main problems any peak detection algorithm has to overcome when being applied to both sinus rhythm and cardiac arrhythmias. Additionally, poor signal-to-noise ratio (SNR) of the PPG signal caused by motion artifacts is another main problem affecting peak detection accuracy for the above-listed heart arrhythmias even after removal of noisy segments.

In this paper, we developed novel peak detection algorithms and compared it with a typical previously developed peak detection method [4] to show that PPG signals from a smartwatch could be used to passively and near-continuously monitor for pulse irregularity suggestive of AF. Our algorithms include an automated approach to detect

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motion artifacts followed by a PPG peak detection algorithm that is accurate and effective for variety of cardiac rhythms including normal sinus rhythm, AF, PAC and PVC; these capabilities have not been demonstrated in any publications to date.

II. Materials and Methods

A. Dataset

16 participants (13 male and 3 female) ranging in age from 63 – 88 years old participated in the smartwatch study at the ambulatory cardiovascular clinic at University of Massachusetts Medical Center (UMMC). Among all participants, 11 had sinus rhythm and 5 with cardiac arrythmia. This study was approved by the University of Massachusetts Medical School (UMMS) Institutional Review Board (UMMS IRB #H00009953). Reference ECG and smartwatch data were measured simultaneously from the chest and a wrist using a 7-lead Holter monitor (Rozinn RZ153+ Series, Rozinn Electronics Inc., Glendale, NY, USA) and a smartwatch (Simband 2, Samsung Digital Health, San Jose, CA, USA (henceforth referred to as simply as Simband)), respectively. One channel of the 3-channel Holter ECG signals was used as the reference for estimation of heart rates, which is sampled at 180 Hz. Only the 5^{th} PPG channel (green LED color, wave length 520-535 nm) among all 8-channel Simband PPG signals was used for data analysis since it consistently provided the best signal quality. Three axis accelerometer (ACC) signals were also recorded on Simband, and both PPG and ACC signals are originally sampled at 128 Hz and were then down sampled to 50 Hz and 20 Hz, respectively. All signals were segmented to a 30-second length with no overlap for peak detection analysis.

B. Experiment Protocol

The study protocol was designed to simulate activities of daily living during smartwatch use and consisted of the following sequences: sit still for 2 minutes, walk slowly for 2 minutes, stand still for 30 seconds, walk quickly for 2 minutes, stand still for 30 seconds, move arms randomly for 2 minutes, and stand still for 30 seconds. Participants were then asked to sit and stand repetitively for 1 minute followed by climbing stairs for 1 additional minute. The last procedure required participants to sit for 1 minute. Fig. 2 succinctly summarizes the above-described protocol. All participants signed an informed consent and study procedures underwent review and were approved by the UMMS Institutional Review Board (IRB ID: H00009953).

C. Peak Detection Methods

The entire procedure of our proposed new peak detection method, defined as the sequence of waveform envelope peak detection (SWEPD), is depicted in Fig. 1. Motion artifact detection [7] is performed as the first step to ensure that PPG data segments are relatively clean. A threshold of the mean of the accelerometer and signal quality index derived from the time-frequency spectra using variable frequency complex demodulation (VFCDM) are used for motion and noise detection. Details of the motion artifact detection algorithm used have been described in [7].

If the PPG data pass the motion artifact detection test, peak

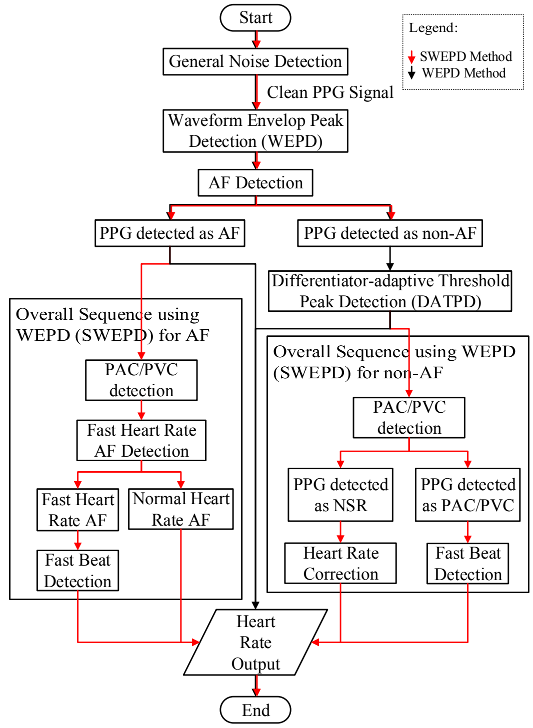

Fig. 1. Flow chart of the proposed SWEPD method, including a new peak correction method.

detections are performed first by using the waveform envelope peak detection (WEPD) algorithm. The WEPD algorithm is similar to standard PPG detection algorithms for NSR [5], but the method differs is that WEPD uses waveform envelope to remove excessive beats caused by the dicrotic notch in NSR data while still retain sensitivity to irregular heartbeats in AF data.

The next step involves AF detection [7] to separate AF from non-AF segments. For AF-detected data segments, the peak detection results from the WEPD algorithm are retained, because WEPD algorithm capture irregular AF beats much better than other published methods on NSR. The next steps are to apply a PAC/PVC detection algorithm followed by classification into AF with rapid ventricular response (RVR) or normal basal heart rate AF. Peak correction is applied for detected AF with RVR peaks. For non-AF detected segments, differentiator-adaptive threshold peak detection (DATPD) algorithm [4] is reapplied on PPG data again, because it is primarily designed to detect normal sinus rhythm. Subsequent steps involve detection of PAC/PVC patterns and if detected, a beat correction algorithm is applied to account for the fast heart rates [8]. Heart rate correction is also necessary if any noisy heart rate is detected in NSR data.

D. Peak Correction Methods

Fig. 2 shows representative PPG data and our proposed peak detection results from sample subjects in our recent study [7]–[9]. Note the Poincaré plots in the right panels of panel (a-f) for each segment type, and Poincaré plot is subdivided into nine quadrants, which represents permutation of all possible heart rate changes [10]. The basal AF heart rates are more confined to the origin in Poincaré plot (Fig.

2(a)) whereas the AF (Fig. 2(e)) and AF with RVR (Fig. 2(f)) are more dispersed. Note also the NSR with motion and noise artifacts have similar dispersed property in Poincare plot (Fig. 2(b)). The mean value of all distances from the Poincaré plot was the best feature in separating the basal heart rate AF from the AF with RVR.

After AF with RVR segments have been detected, the next step is to refine peak detections for AF with RVRs. We label the quadrants associated with each PPG beat using Poincaré plots. Our observation shows that when a heart beat falls in the quadrant two, its heart rate is accurate. However, heart beats that reside in other quadrants (1,3,4,5,7,8), their associated heart beats deviate significantly from the reference heart rates. Hence, these other quadrant beats are all candidates for possible fast heart beat correction. To correct for those candidates' fast heart beats, we look for additional possible local minima or local maxima beats locations in the PPG signal and when they are detected we update their PPG peak locations.

For PAC or PVC arrhythmias as shown in Fig. 2(c) and 2(d), we observe that the associated heart beats reside in the quadrant (6-4-5). The same observations were also noted in prior publications using smartphone and smartwatch derived PPG signals [10]–[12]. Moreover, heat beats with 6-4-5 pattern in Poincare plot and the heart beat associated with the quadrant four is less than 60 BPM, this is indicative of under estimated heart rates. To correct for this under estimation of HR, we use the same peak location updating method as the AF with RVR. Detailed example of PAC/PVC pattern for quadrant '6-4-5' and the corrected peak location are shown in Fig. 2(c) and (d).

For NSR segments, any PPG heart rate that is labelled outside quadrant zero from Poincaré plot is corrected since non-zero quadrant heart beats are mostly caused by motion artifact. The replaced heart rate information is calculated by the averaged heart rate from neighboring clean portion.

III. Results

Among 16 participants' data, 141 30-sec segments are detected as clean data in our noise detection algorithm [7]. 11 participants were identified as NSR, and there were 3 participants with PAC/PVC, 2 participants with basal heart rate AF, and 3 participants with fast heart rate AF. Note that a AF subject could have PPG segments for basal HR AF and AF with RVR, thus, the summed number of participants for each type of arrhythmia exceeded the total number of subjects. Among the total of 141 30-sec segments, we identified 108 segments as NSR with a corresponding 3,393 ECG beats, 13 segments as PAC/PVC with a corresponding 424 ECG beats, 6 segments as normal heart rate AF with a corresponding 230 ECG beats, and 14 segments as fast heart rate AF with a corresponding 643 ECG beats. The average PPG beats per 30-sec segment were: 31.42 beats for NSR, 32.62 beats PAC/PVC, 38.33 beats for the normal heart rate AF, and 45.93 beats for the fast heart rate AF.

Table I shows a comparison of the proposed SWEPD method with differentiator-adaptive threshold detection (DATPD) methods for all arrhythmia types examined in this work. The DATPD method is one of the accurate PPG peak detection algorithms developed by Lazaro et al. [4].

The beat-to-beat average RMSE values of the SWEPD method are all lower than DATPD method for the arrhythmia types listed in Table I. More than 40% reduction is seen in the SWEPD beat-to-beat average RMSE for AF with RVR over the DATPD method, and improvements for other three types or subjects are also significant.

RMSE of the mean HR shown in the second row of Table I also indicate that proposed SWEPD approach provides small error for all rhythm types compared with the DATPD

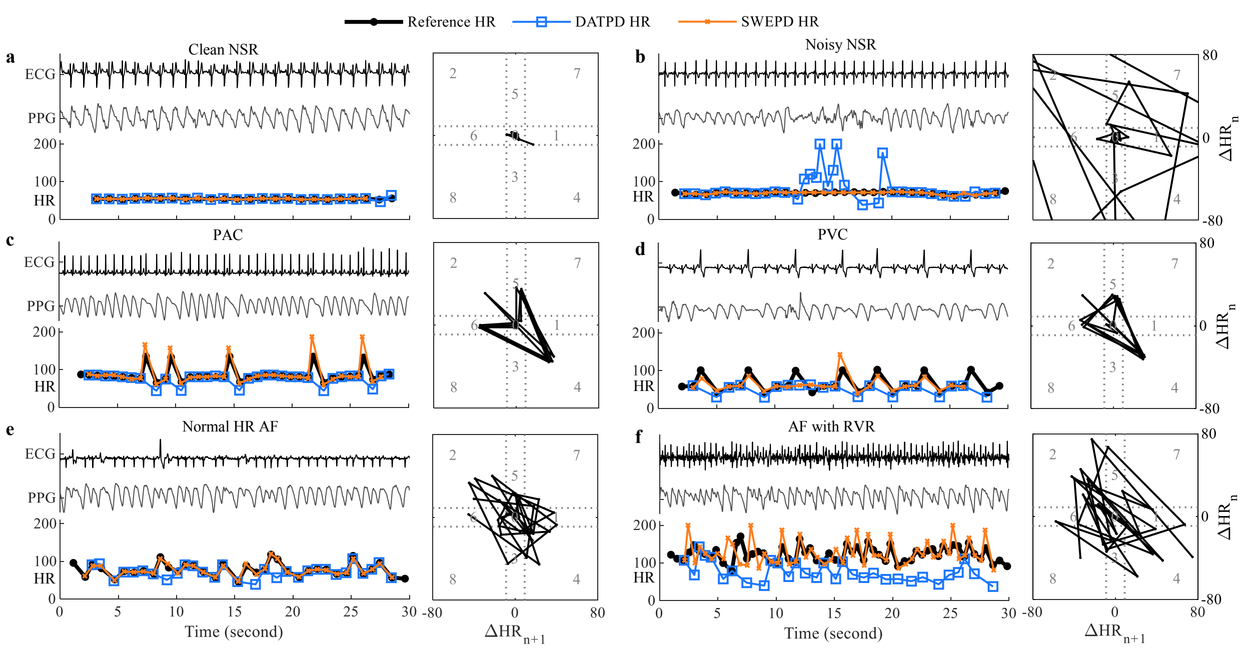

Fig. 2 Representative subjects' 30-sec ECG, PPG and heart rate (HR) smartwatch data with corresponding Poincaré plots. ***a***, ***b***, ***c***, ***d***, ***e***, ***f***: 30-sec segments of ECG (top plot line), PPG (middle plot line) and HR (bottom plot lines—comparing the reference HR (black line), DATPD HR (blue line) and SWEPD HR (orange line)) on clean NSR, noisy NSR, PAC, PVC, normal HR AF, and AF with rapid ventricular response (RVR), respectively.

TABLE I
EVALUATION OF PROPOSED PEAK DETECTION METHODS

Evaluation Method	Subject Type	SWEPD	DATPD
Average beat-to-beat RMSE (BPM/segment)	NSR	2.33	4.95
	PAC/PVC	15.58	28.58
	Normal AF	15.88	20.23
	AF with RVR	35.84	63.99
RMSE of the mean HR (BPM/segment)	NSR	0.51	2.97
	PAC/PVC	4.21	14.18
	Normal AF	10.07	13.47
	AF with RVR	21.60	36.38
Extra Beats (Beats)	NSR	3	32
	PAC/PVC	8	2
	Normal AF	0	0
	AF with RVR	107	3
Undetected Beats (Beats)	NSR	3	34
	PAC/PVC	7	68
	Normal AF	15	23
	AF with RVR	19	230

*SWEPD: Sequence with waveform envelope peak detection; DATPD: Differentiator-adaptive threshold peak detection (Lazaro et al.).

methods. Like beat-to-beat average RMSE, the decrease in the RMSE of the mean HR values is also 40% for the AF with RVR heart rate when compared to the DATPD method. The reduction in the RMSE of the mean HR is even more staggering for PAC/PVC subjects, as 70% decrease is observed with proposed SWEPD detection approach over DATPD method.

Moreover, while the number of extra beats detected by the SWEPD method is higher than DATPD methods especially for AF with RVR, the number of undetected beats is significantly lower for all rhythm types.

IV. DISCUSSION

As shown Table I, compared against DATPD, our SWEPD approach has dramatic improvements in the RMSE and a significant reduction in the number of undetected peaks for all arrhythmias. The reduction of the RMSE for the fast heart rate AF and PAC/PVC rhythms is more than 40% with the proposed SWEPD approach when compared to DATPD. Key reason for this better RMSE result is the number of undetected peaks is much lower with the SWEPD approach when compared to DATPD.

Fewer undetected beats is not only due to the use of an adaptive envelope approach in SWEPD to better discern rapid PPG peaks in arrhythmia with dicrotic notch in sinus rhythm, but also the SWEPD's compensation for the possible fast heart rates that are often associated with PAC/PVC and AF. The aforementioned use of Poincaré plots supported the discrimination of AF with RVR from normal heart rate AF.

Clinically, accurate HR estimation in AF is critical since HR control is a key treatment outcome. As seen in Table I, SWEPD can provide more accurate mean HR information for participants with AF who had high ventricular response rates. Though a reliable mean HR can be obtained from ECG, for PPG signal, it cannot be achieved by prior peak detection algorithms. Using the proposed novel approach, we have made it possible for PPG data that are collected from wearable devices to be used for accurate monitoring of heart rates that may fluctuate in wide ranges due to variety of cardiac arrhythmias.

V. CONCLUSION

In this work, we have shown that our proposed PPG peak detection algorithm provides better peak detection accuracy for sinus rhythm and cardiac arrhythmias. The SWEPD method is based on the waveform envelope method and a novel Poincaré plot feature to automatically correct rapid arrhythmia beats, results in significant reductions in the RMSE values and undetected beats and eventually provides better peak detection accuracy over the compared method (DATPD). The improvement in these values were more than 40% with the rapid heartbeats occurred in PAC, PVC, and in many cases AF.

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