

# Arrhythmia Discrimination using a Smart Phone

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**Abstract**—We propose an arrhythmia discrimination algorithm for a smart phone that can reliably distinguish among normal sinus rhythm (NSR), atrial fibrillation (AF), premature ventricular contractions (PVCs) and premature atrial contraction (PACs). To evaluate the algorithm in clinical application, we recruited 27 subjects with 3 PVC and 4 PAC subjects as well as 20 AF pre- and post- electrical cardioversion. From each subjects, two-minute pulsatile time series from a fingertip is measured using a smart phone. Our arrhythmia discrimination approach combines Poincare plot and Kullback-Leibler (KL) divergence with Root Mean Square of Successive RR Differences (RMSSD) and Shannon Entropy (ShE). Clinical results show that our algorithm discriminates PVC and PAC with accuracy of 100% and 97.87%, respectively.

**Keywords**—atrial fibrillation; Kullback-Leibler divergence; Poincare plot; premature ventricular contraction; premature atrial contraction; Shannon entropy; turning point ratio

## I. INTRODUCTION

Atrial Fibrillation (AF) is the most prevalent arrhythmia worldwide and is increasing with the aging of population. Since AF is associated with heart failure, hospitalization and mortality, AF detection as well as AF treatment is in high demand for the longevity of lives. Since AF can be paroxysmal and asymptomatic in its nature [1], the major challenge is to detect paroxysmal and asymptomatic AF in an efficient way. Currently, undiagnosed AF population is reported to be considerable [2] and frequent monitoring is shown to improve AF detection [3]. Hence, an accurate AF detection method, which is readily available, is highly demanded to improve longevity of lives and reduce healthcare cost. However, current AF algorithms misclassifies non-AF into AF. For example, normal sinus rhythm (NSR) with frequent premature ventricular contraction (PVC) or premature atrial contraction (PAC) episodes can lead to misclassification as AF. This is because the PAC and PVC episodes with NSR mimic the AF dynamics and current AF algorithms are unable to discriminate the dynamics of NSR with PVCs/PACs from that of AF.

For PVC/PAC detection algorithms from ECG signals, template matching is widely used [4]. However, it needs data memory to store templates and requires high computational complexity for template matching between input signal and templates. Due to these limitations, this method is not applicable to real-time computing devices. Our previous AF discrimination algorithm misclassifies NSR with frequent PVC and PAC episodes to be AF. Hence, a new algorithm discriminating PVC and PAC from NSR and AF is needed.

In this paper, we developed an automated algorithm discriminating among NSR, AF, PVCs, and PACs. The developed algorithm is based on a smartphone without additional hardware. Digital camera and flash light embedded in a smart phone monitors skin optically and enables sensing the variability in heart rate signal as shown in Fig. 1 [5]. A 60-beat segment from smart phone is used as an input for our arrhythmia algorithm to discriminate among NSR, AF, PVC, or PAC rhythms. Our previous algorithm is based on statistical metrics of root mean square of successive RR differences (RMSSD) and Shannon entropy (ShE) [6]. We combine Poincare plot and Kullback-Leibler (KL) divergence with RMSSD and ShE to additionally detect bigeminy, trigeminy, quadrigeminy associated with PVCs and PACs as well as to improve accuracy of AF detection. Poincare plot is applied to detect specific patterns such as bigeminy, trigeminy, quadrigeminy associated with PVC or PAC while KL is for discriminating PVCs from PACs. We measured pulsatile time series of 20 NSR, 20 AF, 3 PVC, and 4 PAC subjects using digital camera and flash in an iPhone 4S.

## II. METHODS

### A. AF, PVC, and PAC Databases and Clinical Data Collection

The 20 NSR, 20 AF, 3 PVC, and 4 PAC subjects are recruited by the UMASS Medical Center (UMMC). Pulsatile time series data are collected using an iPhone 4S and the data collection protocol was approved by the Institutional Review Boards of Worcester Polytechnic Institute (WPI) and UMMC, respectively. The subjects are instructed to place their first (index) or third (middle) finger on the camera. Our data collection program automatically turns on flash when we start measurement. During two minutes of measurement, the subjects are instructed to breathe spontaneously in the supine position.

A current prototype of NSR, AF, PVC, and PAC discrimination application for iPhone 4S is shown in Fig 1. A patient can monitor iPhone's measurement procedure on a screen showing blood flow intensity amplitude, heart rate and remaining progress time in real-time. After two minutes of measurement, the application displays heart rhythm identification as well as average hear rate on the screen.

### B. Preprocessing

We record videos of the human fingertip to measure blood flow intensity. From the video, we made use of the green band among the RGB band. This is due to our recent study that the green band among RGB band shows the best signal fidelity.



Fig. 1. A smart phone application for data recording (the application uses the camera lens and illumination to acquire information about heart rate and rhythm).

The sampling rate is 30 frames per second, and the resolution of one frame is 640x480 pixels. Since our experiment shows that the upper half of the video signal (320x480 pixels) has the best signal fidelity, we average the intensity value of the upper half of the frame.

After obtaining the intensity value from each frame, pulse-to-pulse detection is performed by incorporating interpolation, sudden DC change elimination, two stages of band pass filter, derivative rank filter and matching of original peaks.

### C. AF, PVC, and PAC Discrimination

The proposed arrhythmia discrimination algorithm takes a 64 pulse beat series as an input in detecting and determining arrhythmia of AF, PVC, and PAC. Combined with our previous AF detection algorithm [7], the proposed arrhythmia discrimination algorithm discriminates various patterns of PVCs and PACs.

The algorithm first derives RMSSD and Shannon entropy from the pulsatile time series and then compares those statistics with their corresponding threshold values  $RMSSD_{th}$  and  $ShE_{th}$ . If the derived RMSSD and ShE are less than their thresholds, then the subject is determined to have NSR without PAC or PVC. On the other hand, if at least one of the statistics is larger than their threshold values, then the algorithm constructs a Poincare plot. Poincare plot discriminates specific patterns, e.g., bigeminy, trigeminy, and quadrigeminy patterns of PVCs/PACs from the NSR and AF. After finding major patterns of PVCs and PACs, the algorithm updates the pulsatile time series subtract them from the original time series and derive  $RMSSD'$  and  $ShE'$  from the updated pulsatile time series. If at least one of the derived RMSSD and ShE are larger

than their corresponding threshold values, then the subject is discriminated to have AF. Otherwise, the subjects are classified to have PVC or PAC.

The KL determines whether a subject has PVC or PAC. The algorithm makes use of two KL divergences values, obtained from the measured pulses of the unclassified subject as well as trained PVC and PAC data, in its determination. The detailed procedure of the Poincare plot and KL methods are explained in the following section.

#### 1) Poincare Plot

A Poincare plot is used to visualize and quantify the self-similarity of a time series  $x_n$  for  $n=1,2,\dots,N$ . For a two-dimensional Poincare plot,  $(x_{n-1}, x_n)$  is plotted on a two-dimensional Euclidean space. The Poincare plot approach is appropriate in determining the specific patterns of PVCs/PACs due to the observed relation between ECG and pulsatile time series obtained by a smart phone as shown in Fig. 2. The top panel is the ECG data with a PAC episode (noted by an arrow) while a bottom panel is its corresponding pulsatile time series. When a PAC occurs after a normal beat, the pulse signal is elongated and two peaks of the PAC and normal beats are merged into one peak in a pulsatile time series domain. Hence, the difference between consecutive beats ( $\Delta PI$ ) during a PAC/PVC episode is larger than the difference during normal episodes.

Our Poincare plot is divided into six sections with section IDs from 0 to 5. Section 0 is centered on the origin and surrounded by four boundaries,  $x \leq x_{bound}$ ,  $x \geq -x_{bound}$ ,  $y \leq y_{bound}$  and  $y \geq -y_{bound}$ . The “short-short-short” and “long-long-long” PI sequences are confined to this section 0. Section 1 is bounded by  $x > x_{bound}$ ,  $y \leq y_{bound}$  and  $y \geq -y_{bound}$ , and “short-short-long” PI sequences are matched to the section 1. Similarly, we define sections 2 to 5 as follows: section 2 for  $x \leq -x_{bound}$  and  $y \geq y_{bound}$ , section 3 for  $x \leq x_{bound}$ ,  $x \geq -x_{bound}$

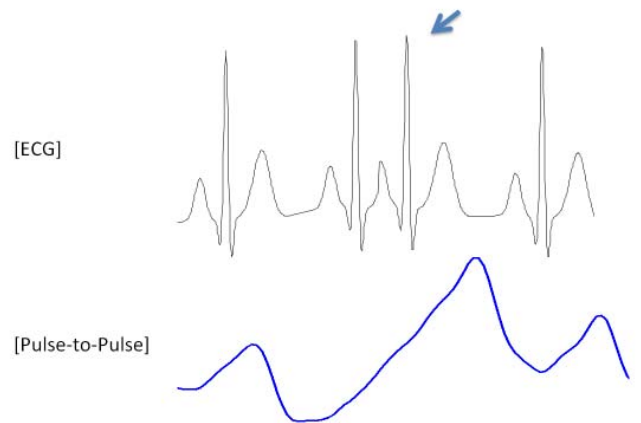


Fig. 2. ECG RR intervals versus pulse-to-pulse intervals from an iPhone 4S for a PAC subject. A PAC episode has longer pulse interval and larger amplitude compared to a NSR episode.

and  $y < -y_{\text{bound}}$ , section 4 for  $x > x_{\text{bound}}$  and  $y < -y_{\text{bound}}$ , section 5 for  $x > -x_{\text{bound}}$  and  $y > y_{\text{bound}}$ , and section 6 for  $x < -x_{\text{bound}}$  and  $y < y_{\text{bound}}$ . The section boundaries  $x_{\text{bound}}$  and  $y_{\text{bound}}$  for  $x$  and  $y$  axis are set considering the pulse time series interval dynamics of NSR, Af, PVC, and PAC subjects. Then, these six sections covers two-dimensional Euclidean space and every combination of three consecutive PIs, i.e., “short-short-short” and “long-long-long” for section 0, “short-short-long” for section 1, “short-long-short” for section 2, “long-short-short” for section 3, “long-short-long” for section 4, “short-long-long” for section 5, and “long-long-short” for section 6.

Hence, NSR’s Poincare plot is plotted within the sections 0 since NSR has regular R-R intervals (RRIs) and its corresponding PI sequence is “short-short-short-...” with small variance. On the other hand, AF’s Poincare plot is irregularly spanned over 6 section. This is because AF has irregular RRIs and corresponding PI sequence are irregular with high variance.

For PVCs and PACs, we define that PAC that occurs every 2nd, 3rd, and 4th pulse, as the bigeminy, trigeminy, and quadrigeminy, respectively. For PVC/PAC quadrigeminy, the PI sequence is “short-short-long-short-short-long-...” where long PI exists every 3rd PI. Hence, its Poincare plots trajectory has a regular pattern of triangle spanning sections 1, 2, and 3. Similarly, the PVC/PAC trigeminy has a periodic PI sequence of “short-long-short-long-...” where short and long periodically oscillates. Hence, its Poincare plot also oscillates between sections 2 and 4. The patterns of quadrigeminy and trigeminy are specific compared to the patterns of NSR and AF. The PVC/PAC bigeminy shows similar pattern with NSR in that their paths are within section 0. However, the bigeminy can be discriminated from NSR using the observation that the bigeminy has longer PI and larger amplitude than NSR.

We applied these patterns of bigeminy, trigeminy, quadrigeminy of PVCs/PACs to discriminate them from NSR and AF since these patterns are regular and discernible from those of NSR and AF.

## 2) Kullback-Leibler Divergence

The KL divergence is used to measure the difference between probability distributions  $p(x)$  and  $q(x)$ , and is defined by:  $KL(q \| p) = -\int p(x) \log \left\{ \frac{q(x)}{p(x)} \right\} dx$ . The KL divergence approach is appropriate for determining whether the unclassified PVC/PAC from Poincare plot is PVC or PAC due to the specific characteristics of PVC and PAC pulses. We first build  $p_1(x)$  and  $p_2(x)$  from the PVC and PAC training pulses, respectively. We then construct  $q(x)$  from the unclassified PVC/PAC pulse measurement data. We determine the pulse of  $q(x)$  is PVC if  $KL(q \| p_1)$  is smaller than  $KL(q \| p_2)$ . Otherwise, the pulse is determined to be PAC.

The representative PVC pulse  $p_1(x)$  and PAC pulse  $p_2(x)$  obtained from PVC and PAC subjects have clear difference. Hence, the unclassified PVC/PAC data from Poincare Plot can

be classified into PVC or PAC based on KL divergence method with  $p_1(x)$ ,  $p_2(x)$  and  $q(x)$ .

## D. Performance Evaluation

The performance of the proposed arrhythmia discrimination for smart phone is evaluated with PAC and PVC as well as NSR, AF, PVC and PAC subjects. We set the thresholds  $RMSSD_{\text{th}}$  and  $ShE_{\text{th}}$  based on ROC curve having the largest area, and set the boundaries of Poincare plot reflecting the NSR, AF, PVC, and PAC training data. We evaluate our discrimination algorithm in terms of sensitivity, specificity, and accuracy.

## III. RESULTS

Using an iPhone, the pulsatile time series of 20 NSR, 20 AF, and 3 PVC, 4 PAC subjects are measured at UMass Medical Center [6]. We set the threshold values of RMSSD and Shannon entropy by  $RMSDD_{\text{th}} = 0.1300$ ,  $ShE_{\text{th}} = 0.7913$ , respectively. Moreover, the boundary values of Poincare Plot are set to  $x_{\text{bound}} = 0.1$  and  $y_{\text{bound}} = 0.1$ . Sensitivity, specificity and accuracy of the proposed arrhythmia discrimination algorithm is obtained. Our arrhythmia discrimination algorithm with the Poincare plot and KL divergence method combined with statistical metrics of RMSSD and ShE shows an sensitivity of 100% in detecting PVCs and PACs. For the discrimination of PVC, the algorithm shows specificity and accuracy of 1.0000 and 1.0000, respectively. Similarly, the proposed algorithm discriminates PAC with specificity and accuracy of 0.9767 and 0.9787, respectively.

## IV. DISCUSSION AND CONCLUSION

In this paper, we have shown that NSR, AF, PVC, and PAC can be discriminated from pulsatile signal of the fingertip obtained by a smart phone. Considering that significant number of AF episodes can be paroxysmal and asymptomatic, arrhythmia discrimination algorithms, which are accurate, readily available and cheap, are in a high demand. With growing prevalence of smart phone, our approach using a smart phone in discriminating arrhythmia can address the needs to monitor arrhythmia in an efficient way. Specifically, since our smart phone-based approach does not required additional hardware such as ECG sensor, it is cost-effective and readily available. The proposed arrhythmia algorithms for smart phones performs AF detection with high accuracy and discriminates PVC and PAC with their specific types. Further study will evaluate usability of our algorithm in a diverse cohort of patients.

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