Wrist-Located Optical Device for Atrial Fibrillation Screening: A Clinical Study on Twenty Patients

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Abstract

This study aims at evaluating the performances of a wrist-located device to detect atrial fibrillation (AF) based on photoplethysmography (PPG) technology. Twenty patients referred for catheter ablation of cardiac arrhythmias in whom episodes of sinus rhythm (SR) and AF coexisted were screened. Screening included a 12-lead electrocardiogram (ECG) and a PPG device placed at the wrist measuring cardiac pulsatility by means of infrared light. While reference cardiac interbeat (RR) intervals were obtained from the analysis of the ECG signals, RR intervals from the PPG signals were estimated by detecting systolic downstrokes on the optical waveforms. Classification of SR versus AF epochs was obtained via a support vector machine to which features extracted on 10-second windows were provided. Extracted features included mean, standard deviation, minimum, and interquartile range of RR within an epoch. A total number of 2213 epochs (1927 of AF, 286 of SR) were analyzed, providing classification accuracy of 93.85% for the PPG-based classifier and 98.93% for the ECG-based classifier. These preliminary results suggest that a wrist-located PPG-based monitor might be eligible for future screening of AF in large populations.

1. Introduction

Since the introduction of portable devices in 1957 by Dr Norman Holter, ambulatory electrocardiogram (ECG) monitors have been extensively used for arrhythmia detection, prognosis, and assessment of efficacy of antiarrhythmic therapy [1]. The global market for Holter monitoring systems represents thousands of millions of U.S. dollars and is expected to increase over the next decade [2]. Key factors of such increase are the rapid rise in the number of patients suffering from cardiovascular diseases, aging population, and the introduction of innovative products. These innovations have been triggered by new ECG-based tools and the improvement of medical device performances in terms of volume, battery lifetime, recording capacity, waterproofness, *etc*.

Atrial fibrillation (AF) is the most common cardiac arrhythmia, affecting more than 10.0% of the population over 80 year old [3]. AF can be symptomatic (palpitations, chest pain, etc.) or asymptomatic and hence difficult to diagnose in its early stage (paroxysmal). The gold standard tools for the diagnostics of AF are surface and implantable ECG monitors. However, despite recent progresses to make ECG devices portable, this technique is quite costly and cumbersome for the screening of AF in large populations. Alternative diagnosis tools are needed.

Over the last decade, photoplethysmography (PPG) has found widespread clinical and consumer electronic applications. PPG is an optical measurement technique that requires two opto-electronic components to be placed on the skin surface: a light source to illuminate the tissue, and a photodetector to measure small variations in light intensity associated with changes in perfusion of the underlying tissue [4]. The interaction of light with biological tissue is complex and includes optical processes such as multiple scattering, absorption, reflection, transmission and fluorescence [5]. PPG signals are especially interesting because they are made available by low-cost and comfortable sensors. Nowadays, PPG technology is used in many commercial solutions such as pulse oximeters, vascular diagnostic tools, digital blood pressure measurement systems and in numerous smartphone applications [6, 7].

While more than 10 years of research and development have been necessary to bring the PPG technology into actual low-power solutions [8–10], a major question remains unanswered: is the cardiac activity information provided by wrist-located PPG sensors accurate enough to substitute ECG-based solutions on the ambulatory screening of large populations? The aim of this study is to provide first

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experimental data to support this hypothesis.

2. Methods

The clinical study described in this section is compliant with all relevant Swiss ethics, regulation and institutional policies, and in accordance with the tenets of the Helsinki Declaration. Informed consent was obtained from all individuals before enrolment at Lausanne University Hospital (CHUV).

2.1. Data

Signals were recorded on twenty patients admitted for AF or ventricular tachycardia during standard diagnostic procedures used by the CHUV's Electrophysiology Laboratory before catheter ablation intervention. For each patient, 12-lead ECG signals were acquired at 2 kHz by a commercial electro-physiology system (Siemens Sensis), and PPG waveforms were acquired by a proprietary wrist-based device embedding reflective infrared sensors sampled at 21.33 Hz. ECG signals were further analyzed by clinical experts, providing annotations of sinus rhythm epochs (SR), regularly paced rhythm epochs, irregularly paced rhythm epochs, and AF epochs. Regularly and irregularly paced rhythms epochs were excluded from the analysis.

2.2. Pre-Processing

Data pre-processing consisted on estimating and aligning interbeat intervals when extracted from ECG and PPG raw signals. Initially, position of heartbeats on ECG signals was extracted from R-wave detection as directly provided by the commercial electro-physiology system. The arrival of a pressure pulse in the small arteries located in the vicinity of the optical sensor produces an increase of tissue blood volume that results in an augmentation of the light absorption, leading to a reduction of the measured optical signal amplitude (systolic downstroke). Therefore, position of heartbeats in PPG signals was performed by detecting the systolic downstroke of each heart-beat waveform.

For this study, systolic downstrokes were identified as the zeros of the PPG signal second derivative, when such curvature changed from positive to negative values. Initially, a second order derivative was calculated by applying a finite impulse response filter to the raw optical signal. The coefficients of the filter were given by:

$$\begin{aligned} dd_n = [&1/3, 1/3, 1/3, -2/3, -2/3, \ldots \\ &-2/3, 1/3, 1/3, 1/3] \circ \text{hanning}(9) \end{aligned} \quad (1)$$

where $\circ$ is the element-wise multiplication (Hadamard product) and $hanning(9)$ is a hanning window of 9-sample length. Then, systolic downstrokes were obtained by finding the pairs of samples crossing the zero value of the second order derivative during positive-to-negative transitions. A linear interpolation was applied between these sample pairs to increase the temporal resolution.

ECG- and PPG-based interbeat intervals were then computed from the R-waves and systolic downstrokes by taking the time difference of consecutive events. For each patient, beat-to-beat alignment of the two series of interbeat intervals was then performed. Since many non-cardiac factors such as respiration and body motions corrupt PPG signals, alignment of both series was performed via a dynamic time warping algorithm [11]. The aligned series of interbeat intervals allowed to relate the two time-bases of the recording systems. The relation between these two time-bases was assumed to be modeled by the linear equation

$$\widehat{t_{ECG}} = \alpha \cdot t_{optical} + \beta \quad (2)$$

where $\widehat{t_{ECG}}$ is the estimated time in the ECG system time base corresponding to $t_{optical}$ in the PPG system time base, α is the relative drift of the PPG system clock relatively to the ECG system clock and β is time offset of the two recordings.

For this study, the parameters α and β of equation 2 were estimated by a regression method. Because of the noisy nature of the systolic downstrokes determined from PPG signals, outlier values were removed before the estimation of the parameters of the linear model of equation 2. A random sample consensus (RANSAC algorithm) [12] directly rejected such outliers during the estimation process. During the estimation of the α and β parameters the residual threshold of the RANSAC algorithm was set to one second. Finally, equation 2 was used to transform the time base of the PPG signals to match the time base of the ECG signals. After this time transformation, synchronous pairs of interbeat intervals could be compared as described in the following sections. Expert annotations of rhythm epochs were automatically projected into the same time base, leading to one annotation for each interbeat interval. Figure 1 illustrates typical examples of aligned ECG and PPG data, as well as calculated RR intervals.

2.3. Feature extraction

The synchronized interbeat time series were segmented in overlapping time windows of 10 seconds: one 10-second time window for each detected beat, leading to a total number of 2213 epochs. For each time series, the following features were calculated at each window:

- feature #1: mean value of the interbeats intervals;
- feature #2: minimum value of the interbeat intervals;
- feature #3: median value of the interbeat intervals; and
- feature #4: interquartile range of the interbeat intervals.

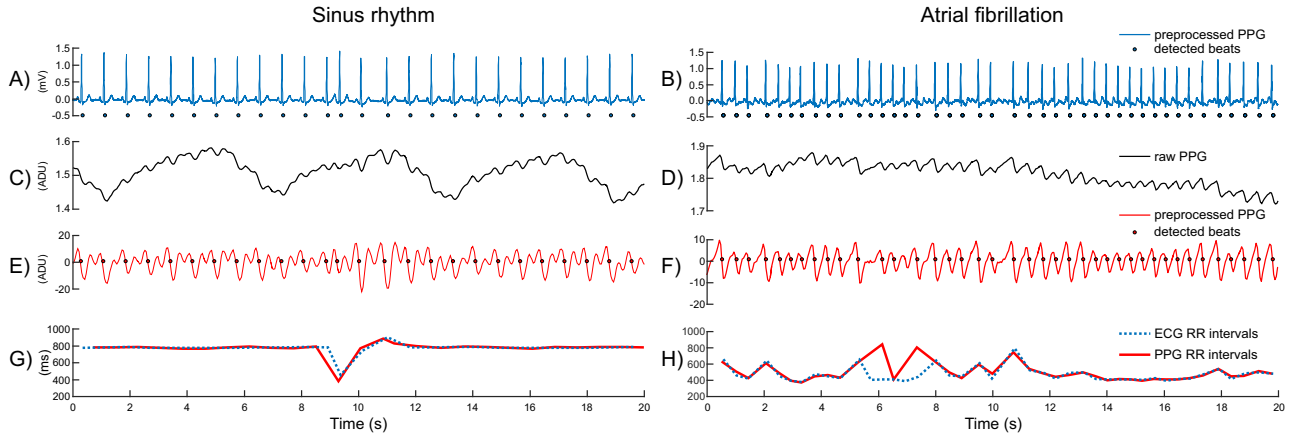

Figure 1. Illustrative examples of signals acquired during the present study, depicting SR conditions (left panel) and AF episodes (right panel). A) and B) illustrate raw ECG signal and the time indexes of their corresponding detected R-waves provided by the electro-physiology monitor. C) and D) illustrate raw PPG signals acquired at the wrist (note the low-frequency respiration component). E) and F) illustrate the preprocessed PPG signals and the time indexes of their corresponding detected systolic downstrokes. G) and H) illustrate the associated interbeat intervals estimated from the ECG (dotted blue lines) and PPG signals (bold red lines).

2.4. Classification

The previously-described feature extraction algorithm created a set of four ECG-related features and a set of four PPG-related features for each annotated epoch. These sets of feature values were used to train a Support Vector Machine classifier with a linear kernel to separate the AF from SR feature sets. To avoid overfitting, a leave-one-out procedure was used to assess the performance of the classifier.

3. Results

Overall performances of the implemented classification algorithm when applied to ECG and PPG signals are provided in Table 1. Positive and negative classifier results are associated to AF and SR, respectively.

Table 1. Classification of AF (positive event) and SR (negative event) episodes

	ECG	**PPG**
True positives	1926	1913
False positives	13	124
False negatives	12	14
True negatives	287	162
Sensitivity	0.9938	0.9938
Specificity	0.9600	0.5664
Accuracy	**0.9893**	**0.9376**

4. Discussion

The results of the present study (see additional material in [13]) constitute to the best of our knowledge a first clinical evidence of reliable AF detection using PPG sensors at the wrist. The high values of sensitivity (99%) showed in Table 1 demonstrates the potential of a wrist-located AF classifier using PPG technology. Unfortunately, by classifying beats individually (without any memory consideration), the classifier was exposed to low level of specificity (57%): there is thus a large room for improvement on this direction. Additionally, the training of the classifier on biased data (number AF beats number SR beats) also affected specificity negatively.

The analysis of the recorded data has pointed at the fact that the addition of features based on variation of waveform morphologies (as presented in [13]) might be necessary to achieve improved algorithm performances: typical data segments depicted in Figure 1 illustrate this challenge. We observed that for a large number of AF epochs, pathological PPG waveform morphologies were recorded: see by instance Figure 1 D) and F). We hypothesize that AF leads to changes in hemodynamics such as reduced stroke volume (followed by a reduction in systemic blood pressure) and a pooling of venous blood [14], leading to such pathological waveform morphology. In addition variations of PPG waveform amplitudes were observed on numerous episodes during SR as well as during AF. Illustration of such amplitude variations can be observed in Figure 1 C) around the 10^{th} second and over the entire signal of Figure 1 F)). This might reflect stroke volume variations caused by short and long recovery episodes (consecutive

short and long interbeat intervals) combined with the compensation of the sympathetic vasoconstriction due to peripheral pressure increase. This phenomena is expected to modulate PPG signals and create the observed low frequency component. However, although missing beats and false positive PPG detections were observed during AF episodes (see two missing beats around the 6^{th} and 7^{th} seconds in Figure 1 F) and H)), general trend of the time series of PPG interbeat intervals were similar to those obtained from ECG signals (see bold red and dotted blue lines in Figure 1 G) and H)).

Concerning the overall classification performance, it is interesting to compare AF versus SR classification performances shown in Table 1 to a recently published study, which compared AF detection performance between permanent pacemaker (accuracy of 0.9913) and implantable cardiac monitors (accuracy of 0.7219) [15]. The detection of AF in these two devices was also based on features extracted from time series of interbeat (or RR) intervals.

Based on these preliminary PPG-based wrist-located devices appear to potentially perform similar performances to implantable cardiac monitors when screening AF. The advantages of the PPG disruptive technology are numerous: ranging from its non-invasivity and limited cumbersomeness, to its extremely reduced cost. Adding to these facts the expected high patient acceptance of such a device, we expect PPG-based wrist-located devices to revolutionize the screening of AF in large populations. Nevertheless, further work is still required to improve achieved performances, in particular concerning the PPG preprocessing during AF, the cardiac beat detection from PPG atypical waveforms, and the extraction of features from time series of interbeat intervals [13].

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