Atrial Fibrillation Detection Using the PulseOn Technology

Abstract— **Atrial fibrillation (AF) is the most common type of cardiac arrhythmia. Although not life-threatening itself, AF significantly increases the risk of stroke and myocardial infarction. Current tools available for screening and monitoring of AF are inadequate and an unobtrusive alternative, suitable for long-term use, is needed. This paper evaluates an AF detection algorithm based on photoplethysmogaphic (PPG) signals. Inter-beat intervals (IBI) extracted from the PPG signals are used as inputs. As IBI estimation is highly sensitive to motion or other interferences, unreliable IBI are automatically detected and discarded. The algorithm is evaluated on two sets of data, of 45.48 and 248.30 hours, respectively. For both sets, the sensitivity is above 98% and the specificity above 99%. These results show that wrist PPG is suitable for long term monitoring and AF screening. In addition, this technique provides a more comfortable alternative to ECG devices.**

I. INTRODUCTION

Heart rate variability (HRV) provides information about a person's health status, and can be used for both wellness and clinical applications, such as atrial fibrillation (AF) detection.

Atrial fibrillation (AF) is the most common type of cardiac arrhythmia, affecting more than 10% of the population above 75 years old [1]. Even if AF may display symptoms such as heart palpitations, shortness of breath, or lightheadedness [2], it is asymptomatic in at least one third of the cases. However, AF is associated with increased risk of myocardial infarction, heart failure, and stroke. As a result, timely and reliable detection of AF is an essential part of both treatment and pre-emptive therapy.

The most common techniques for AF detection are based on the ECG technology. The used devices can be in-hospital monitors, 24/48 hours ambulatory Holter monitors, event recorders, or electrode patches. However, these methods suffer from several limitations. Hospital recordings are usually of short duration and might not detect cases such as paroxysmal atrial fibrillation. 24/48 hour Holter monitors only detect AF in 30% to 60% of the cases [3]). Some devices are cumbersome and can limit mobility. If worn for longer durations, the electrodes can easily become uncomfortable and possibly cause skin irritations. In addition, dry skin or poor skin contact often disturb chest strap based HRV monitoring. Monitoring tool obtrusiveness and high cost can also lead to low patient acceptance rate. Thus, there is a clear demand for new technologies, which do not interfere with a person's comfort.

Photoplethysmography (PPG) provides an alternative method for HR and HRV monitoring [4]. Instead of measuring the heart electrical signals, this technology uses light signals to monitor the heart activity. Given that the measuring device can be integrated in a wrist-band, the wrist PPG technology, if proven accurate enough, would provide tremendous benefits in both clinical and home monitoring scenarios: a comfortable, wearable, unobtrusive measurement method suitable for long-term monitoring. Besides analyzing life-style, sleep, and stress levels, it could also be used in the screening of various cardiac anomalies.

AF detection from PPG signals has not been extensively studied, but there is increasing interest in this domain. Proposed methods investigate the possibility of extracting inter-beat intervals (IBI) from PPG signals, usually finger or wrist-based, and taking the decision based on IBI series statistics. Commonly used features are IBI dispersion, sample entropy, distribution histograms, or successive IBI probabilities. Others analyze the PPG signal power spectrum distribution or PPG waveform similarities to discriminate between AF and sinus rhythm (SR) cases [5, 6, 7].

In this paper, we present the core technology of PulseOn (www.pulseon.com) optical HR monitoring and evaluate its accuracy for AF detection.

II. PULSEON TECHNOLOGY

A. Optical Heart Rate Monitoring

Optical HR monitoring is based on the PPG technique. The skin is illuminated with a LED and a photodetector measures the intensity of the transmitted or reflected light. This intensity depends on the blood volume in the skin capillaries and the vasculature deeper in the tissue, which, in turn, vary with the pumping actions of the heart. Thus, by analyzing the light intensity, we can determine both HR and IBI.

One of the main problems of PPG measurement is that the useful signal is corrupted by ambient light and other electromagnetic radiations (ambient light artefacts), and by gravity and by voluntary and involuntary subject movements (motion artefacts). The ambient light artefact influence can be measured using multiplexing techniques and eliminated by subtractive techniques. An efficient way to reduce the motion artefacts is to use a motion reference signal provided by an accelerometer and to perform signal enhancement afterwards. In this way, we may obtain reliable HR estimates even under intense physical activities.

This technology has already been used for HR estimation in both medical and wellness domains. However, because IBI estimation is less reliable in the presence of noise, its usability for HRV monitoring or AF detection still needs to be validated.

B. PulseOn Technology

The PulseOn optical heart rate (OHR) solution uses multiple light wavelengths and optimally matched LED-photodetector distances to allow the measurement of blood flow at different tissue depths. The mechanical design of the housing and the strap provides a stable skin-sensor contact in all conditions. This reduces the artefacts without compromising the comfortable use.

The device used in this study is the PulseOn Medical Tracker, shown in Figure 1. It is a wearable wristband OHR monitor designed for clinical use, monitoring HRV, and screening and monitoring arrhythmias and sleep apnea. Easy to use and comfortable to wear for up to one week without recharging, it enables true long term data collection. Additionally, it can log general lifestyle related user data such as sleep quality, steps, and energy expenditure, to aid in developing a more complete view into a person's everyday well-being. The data can be accessed by the health care professional through web based tools for in-depth analysis. The light weight (35g including strap) further reduces the artefact risk and guarantees that the device is not cumbersome and will not interfere with the user's daily activities, thus having a high acceptance rate. Because the device is designed for clinical applications, it does not have a display in order not to distract the users. The sport and wellness version (PulseOn OHR Tracker) is shown in Figure 2.

Figure 1.   PulseOn Medical Tracker device

Figure 2.   PulseOn OHR Tracker for sport and wellness

The HR estimation algorithm applies the accelerometer data to reduce the motion artefacts and provide accurate HR estimation for a range of activities from rest or daily office routine to intensive training. Added to this, the acceleration data is used to determine activity related parameters such as step or calorie count.

In addition to most available optical heart rate monitors, PulseOn also computes the beat-to-beat intervals with millisecond precision. The algorithm has been scientifically validated on subjects of different ages and health conditions [9, 10]. In the absence of motion, the mean absolute error with respect to RR intervals (RRI) obtained from ECG reference is below 8 ms for sinus rhythm (SR) subjects and below 15 ms for subjects suffering of different arrhythmias. This is considerably lower than the difference between consecutive beats and in close agreement with the reference. However, optical IBI estimation is not reliable in the presence of motion, varying ambient light, or other interference. To overcome this, the PulseOn algorithms automatically detect such situations and screen out unreliable data based on the motion level and the PPG wave morphology. Thus, the risk of incorrect HRV or arrhythmia estimation is minimized.

Besides high accuracy, the PulseOn algorithms are designed for low power consumption and to be run in real-time. This reduces the battery consumption and enables continuous long-term monitoring for up to one week.

III.   TECHNOLOGY VALIDATION

A. Validation Data

The technology is validated on two different data sets. The first set consists of subjects that had undergone surgery immediately prior to the recording and were recovering from the effects of anesthetics. The subjects were classified in two groups, having either continuous SR or continuous AF. The SR group consists of 15 subjects, 8 male, 7 female, 67.5 ± 10.7 years old. The AF group consists of 14 subjects, 6 male, 8 female, 74.8 ± 8.3 years old. The total 23.52 hours for the SR group and 21.96 hours for the AF group. All test subjects gave their written consent to participate after being informed on the purpose of the study. They had the right to withdraw from the study at any time. The study protocol, devices, and documentation were approved by the local ethical review board of Pirkanmaa Hospital District (R17024), the Finnish National Supervisory Authority of Health and Welfare, and the technical department of the hospital. The experimental procedures comply with the principles of the Helsinki Declaration of 1975, as revised in 2000.

This set has the limitation that the data is either SR or AF, without transitions between the two states. To simulate paroxysmal AF, and have a better view of the algorithm performance, we created a new data set by mixing AF and SR data. While the AF intervals came from the above-described group, the SR intervals came from hospital, office, or home recordings. The considered AF interval lengths are between 30 and 500 seconds and the SR interval lengths are between 30 and 900 seconds. Overall, there were 40 sets with lengths between 4 and 9 hours. The total recording duration is 248.3

hours, out of which 64.4 are AF and 183.9 SR. The fact that this data was obtained by artificially concatenating segments from different users makes the estimation potentially more difficult because of high parameter variance, artificially introduced discontinuities, and algorithm convergence time. In the following, we will call these two sets as the hospital-recorded and mixed-data set, respectively.

B. Data Acquisition

Wrist PPG signals were recorded with the PulseOn Medical Tracker or the PulseOn OHR Tracker devices. The device was worn as instructed by the manufacturer, about one finger width from the wrist bone and tightened by the person in charge of data collection so that the skin contact was firm but still comfortable for the whole recording. The IBI and IBI reliability were provided directly by the PulseOn device.

The reference ECG RRI signals were measured with the Bittium Faros (www.bittium.com), Firstbeat Bodyguard 2 (www.firstbeat.com), or GE Carescape B850 monitor (www.gehealthcare.com) devices. The RR intervals (RRI) were obtained from the ECG signals using the Kubios HRV software, version 2.2 (www.kubios.com).

C. Data Analysis

In Figures 3 and 4, we present two examples of ECG and PPG waveforms, and the corresponding RRI and IBI values for the SR and AF cases, respectively, in the absence of noise. We notice the absence of the P-wave in the ECG signals for the AF set, but there is no visible morphological difference in the PPG signal. However, the variation of the IBI values is clearly higher for the AF set, fact which will be considered by the used algorithm.
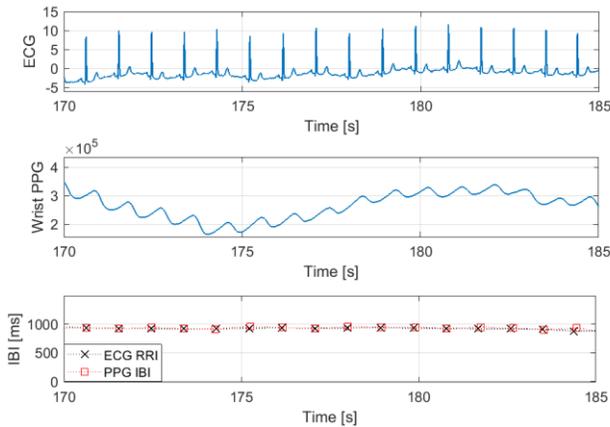

Figure 3.   Example of ECG and PPG waveforms and the corresponding RRI and IBI during sinus rhythm
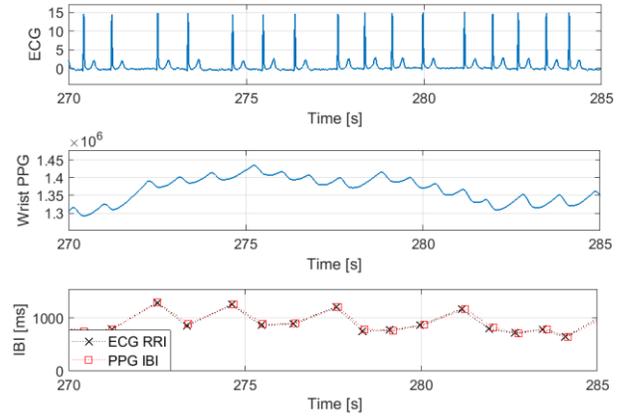

Figure 4.   Example of ECG and PPG waveforms and the corresponding RRI and IBI during atrial fibrillation

The algorithm runs in real-time and its block scheme is presented in Figure 5. The input signals are PPG and 3D accelerometer data recorded by the OHR device. The main processing blocks are:

- IBI extraction:

Estimates the IBI from the raw PPG signals. The accuracy of this method has been validated for both SR and AF subjects of different ages and health conditions in [9, 10]. In the absence of motion, the IBI estimation error relative to the ECG reference is below 1% for SR subjects, and 1.58% for AF subjects [10]. This accuracy is suitable for both HRV analysis and to differentiate between AF and SR.

- Beat validation:

As IBI estimation is not reliable in the presence of noise, it is important to screen out such data. This is done by using both the acceleration signals and the morphology of the PPG signal. A mask is associated to each computed IBI value, indicating whether it is reliable (mask = 0) or not (mask = 1).

- AF detection:

The AF detection algorithm is based on a Markov model approach, similar to the work of Moody and Mark [11]. It operates on sliding windows of 20 consecutive IBI and returns the most likely condition, SR (output > 0) or AF (output < 0). If less than half of the beats from the window are reliable, then the output is set as undetermined, due to the insufficient number of reliably detected IBI (output = 0).

Figure 6 illustrates how the proposed method works. In the 160 - 165 s interval, motion, depicted as variations in the 3D acceleration signal, generates artefacts in the PPG signal. In these situations, IBI estimation is inaccurate, as seen in the comparison with the ECG reference. The beat validation block detects this and marks the beats as unreliable (the IBI mask

from the lower panel is set to > 0). Afterwards, when the movement stops, the PPG signal quality increases and the IBI are considered reliable (the IBI mask is set to 0). Unreliable input beats cause the output of the AF/SR decision block to be set to 0, or undetermined. When the beats are reliable again, the decision is set to SR (> 0). Note that the AF/SR decision appears to be delayed because at least 10 beats out of the last 20 should be reliable for a SR or AF decision to be taken.
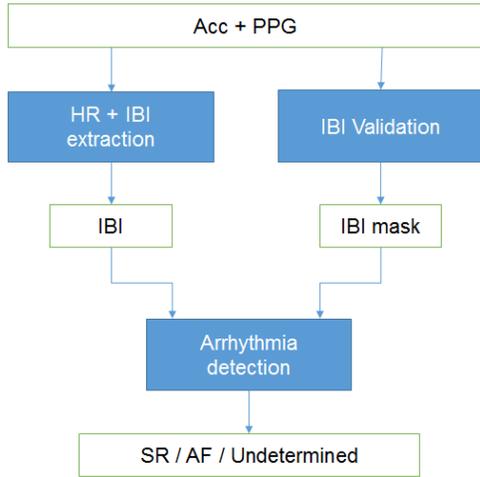

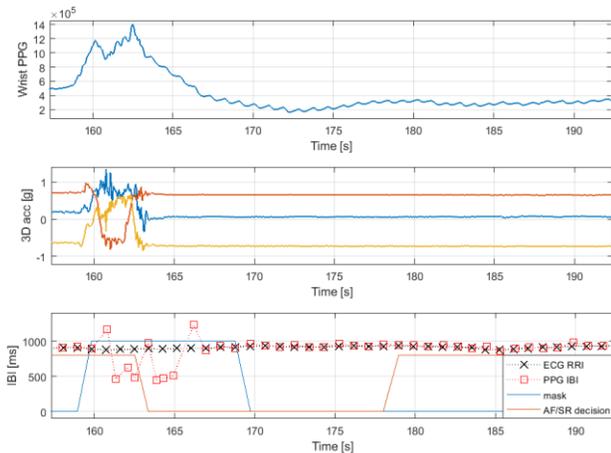Figure 5. Data analysis block scheme

Figure 6. Effect of motion, depicted as variations in the 3D acceleration signal, on the IBI estimation and AF detection from wrist PPG signals

To evaluate the AF detection algorithm, we classify each IBI as AF, SR, or uncertain. The performance is evaluated in terms of sensitivity (percentage of AF data classified as AF) and specificity (percentage of SR data classified as SR). To understand the importance of correctly identifying reliable beats, we compute the statistics in two cases: for all PPG IBI (i.e., all detected beats are considered reliable), and for the proposed method.

IV. RESULTS AND DISCUSSION

The AF detection results are shown in Table I for the hospital-recorded data [12] and in Table II for the mixed-data set. For the first set, the sensitivity for reliable IBI is $98.45 \pm 6.89\%$, and the specificity is $99.13 \pm 1.79\%$. For the mixed-data set, the sensitivity is $98.20 \pm 0.99\%$ and the specificity $99.72 \pm 0.24\%$. In both cases, the results are comparable to or better than what has been reported in previous studies, using either PPG or ECG signals [13]. Figure 7 presents the classification results for 60 minutes of data, containing three AF episodes. The top panel shows the IBI and the mask indicating unreliable IBI. The lower panel shows the AF classification, together with the reference.

The importance of using only reliably estimated IBI is visible in the specificity values. For the hospital-recorded data, the specificity increases from $87.23 \pm 11.13\%$ when including all detected IBI in the statistics to $99.13 \pm 1.79\%$ when including only reliable beats. For the mixed-data sets, the specificity increases from $81.98 \pm 4.43\%$ to $99.72 \pm 0.24\%$. The sensitivity also increases from $96.86 \pm 2.10\%$ to $98.20 \pm 0.99\%$

The performance improvement due to using reliable beats is more visible in the mixed-data set, because it contains more periods of activity. This is also why the percentage of classified IBI is 66.20 ± 4.86, compared to 76.34 ± 19.54 for the hospital-recorded data. It is unavoidable that unreliable data needs to be discarded to obtain more accurate estimates, but this is naturally preferred to taking a wrong decision. For example, for the mixed-data set, screening out unreliable IBI reduces the false arrhythmia alarm rate from 18.02% to 0.28%.

TABLE I.

AF/SR CLASSIFICATION RESULTS FOR THE HOSPITAL-RECORDED DATA

		SR [%]	AF [%]	Classified intervals [%]
All IBI	SR	87.23	12.77	100
	AF	1.08	98.92	
Reliable IBI	SR	99.13	0.87	76.34
	AF	1.55	98.45	

TABLE II.

AF/SR CLASSIFICATION RESULTS FOR THE MIXED-DATA

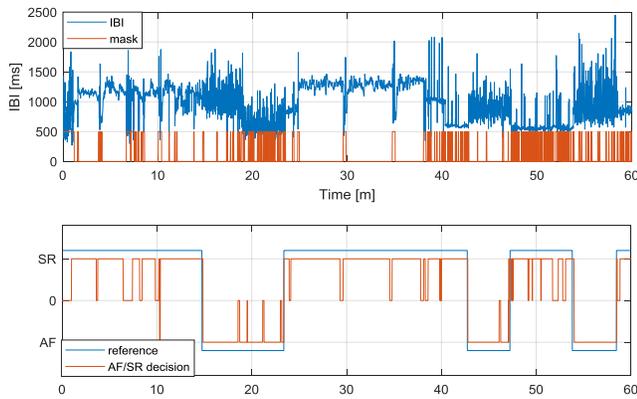|		SR [%]	AF [%]	Classified intervals [%]
All IBI	SR	81.98	18.02	100
	AF	3.14	96.86	
Reliable IBI	SR	99.72	0.28	66.20
	AF	1.80	98.20	

Figure 7. Algorithm output for 60 minutes of data containing three AF episodes

V. CONCLUSION

This study evaluates the accuracy of the PulseOn AF detection. The algorithm uses wrist PPG and acceleration signals, and runs in real-time. On sets containing continuous AF or SR data, the sensitivity is $98.45 \pm 6.89\%$ and the specificity $99.13 \pm 1.79\%$. On sets containing both SR and AF data, the sensitivity is $98.20 \pm 0.99\%$ and the specificity $99.72 \pm 0.24\%$.

This high level of accuracy is due to both accurate IBI estimation and automatic detection of unreliable data. Considering only the reliable IBI for analysis, the specificity increases from $81.98 \pm 4.43\%$ (when considering all IBI) to $99.72 \pm 0.24\%$ for the mixed-data set. This ensures that the false alarm risk is minimized.

To conclude, the study confirms that the PulseOn wrist PPG technology is suitable to detect AF, with accuracy comparable to or even better than ECG devices. Considering that the measuring device is unobtrusive and comfortable to wear, this provides a promising alternative to current monitoring technologies, and an important step towards wearable, comfortable, 24/7 monitoring.

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