Performance of Noncontact Video-based Detection of Pulse Rate and Atrial Fibrillation on the iOS Platform

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Abstract

We developed a video-based monitoring technology to detect atrial fibrillation and pulse rate without the need for a patient to adopt a dedicated wearable device. It is a low-cost, software-only solution running on smart devices. The technology minimises requirements for patient compliance with recording procedures since it passively monitors patients while they use their personal device for other purposes. In the past, we reported results for Android based devices (tablets and smartphones). In this work, we investigate performance of an implementation of the technology on the iOS platform using a personal iPhone X smartphone device. Our analysis is based on a clinical validation study involving 22 patients diagnosed with paroxysmal and persistent Atrial Fibrillation. Results demonstrate very high accuracy in estimating pulse rate (97% of estimated pulse rate values have no more than 5 BPM deviation from reference heart rate), as well as specificity and sensitivity of 0.88 and 0.80 respectively in detection of atrial fibrillation.

1. Introduction

Detecting the recurrence of *Atrial Fibrillation* (AF) at an early stage of the disease is likely to improve patients' prognoses and slow disease progression. Once diagnosed, many AF patients receive heart rhythm regulating medication. Tracking the impact of such drugs by persistently measuring *Heart Rate* (HR) is important to assess their efficacy and facilitate drug titration.

Current cardiac monitoring solutions often present challenges, including their cumbersome nature, limited monitoring periods of just a few weeks, the necessity for patients to invest in new and unfamiliar equipment, and the reliance on patient compliance with self-conducted monitoring procedures conducted away from a healthcare facility and for a long period of time.

Like traditional *PhotoPlethysmoGraphy* (PPG), *VideoPlethysmoGraphy* (VPG) captures a pulsatile signal from a patient's face [1-18]. It does so by capturing the modulation of ambient light reflected from one's face due to changes in blood volume (hemoglobin) in the upper layers of the skin. Past work on VPG investigated its performance compared to PPG and ECG devices. Some examples can be found in [3-8]. It was shown that under certain reasonable conditions (ambient light, stillness, and camera specifications), VPG offers a reliable alternative to PPG and ECG.

We make use of the VPG monitoring paradigm to create HealthKam AFib - a digital health solution for cardiac monitoring that leverages a common characteristic shared by all: access to and utilization of smartphones. HealthKam AFib is comprised of a downloadable APP and a remote sever. The APP operates in the background, while the user makes regular use of the personal device (reading emails, going on social networks, etc.) to capture signals using the front facing camera of the device. The user can also initiate an on-demand measurement. No pictures or videos are taken in the process, so complete user privacy is preserved. Anonymized captured data is sent to the cloud, where sophisticated algorithms are used to estimate *Pulse Rate* (PR) and detect AF. The resulting indications are sent back to the APP for presentation to the user and for tracking monitoring history. Other features offered by HealthKam AFib include generating a report and sending it to a caregiver, setting reminders and accessing educational material. Figure 1 depict some of the user interface screens of the HealthKam AFib APP, and Figure 2 presents the possible responses to a measurement being taken on-demand.

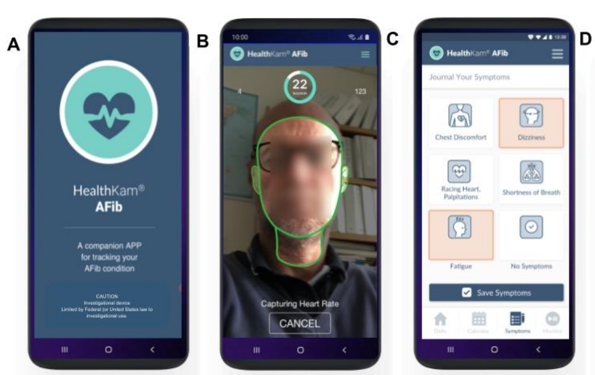

Figure 1: Main user interfaces of the Healthkam AFib APP.

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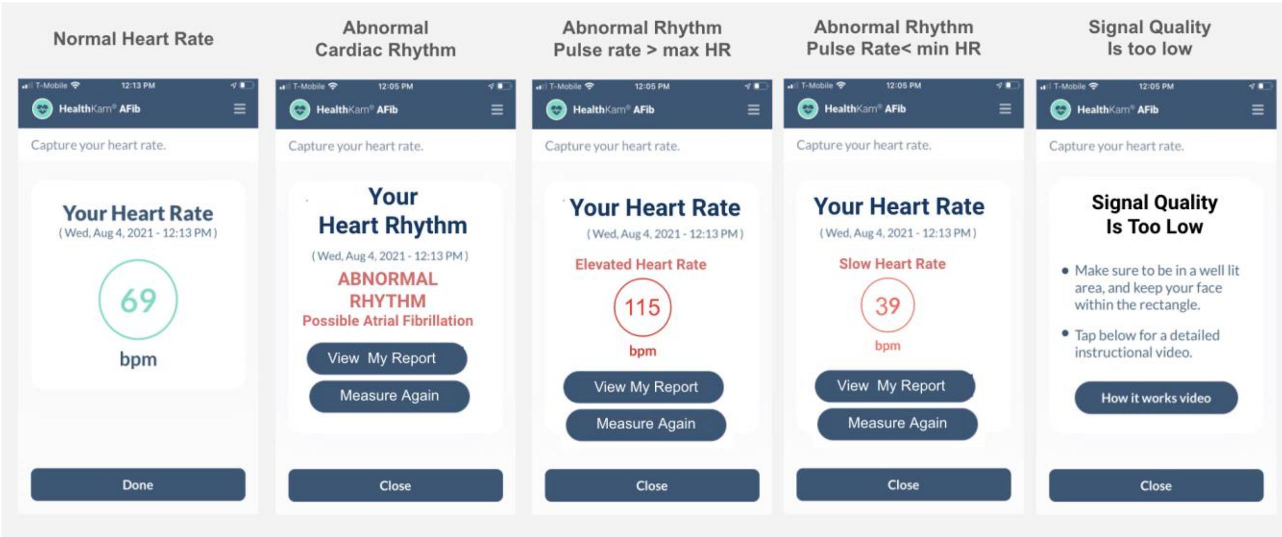

Figure 2: Healthkam AFib screenshots with the five possible outcomes of a VPG measurement.

	Female (N=16)	Male (N=44)	P-value
Age (yrs)	71 ± 8.9	66 ± 10	0.091
Weight (kg)	78 ± 19	98 ± 16	0.003
Height (m)	1.7 ± 0.081	1.8 ± 0.099	<0.001
BMI (kg/m2)	28 ± 5.8	31 ± 5.4	0.117
Syst BP (mmHg)	120 ± 18	130 ± 13	0.301
Diast BP (mmHg)	75 ± 10	80 ± 14	0.249

	Female (N=16)	Male (N=44)
AF type		
Long standing persistent	1 (6.3%)	5 (11.4%)
Paroxysmal	8 (50.0%)	17 (38.6%)
Persistent	1 (6.3%)	6 (13.6%)
Unknown	6 (37.5%)	12 (27.3%)
Permanent	0 (0%)	4 (9.1%)

Table 1: Validation study cohort statistics.

A patient using HealthKam AFib does not need to adopt a dedicated and costly wearable device. By offering a low-cost downloadable solution, HealthKam AFib minimizes the impact of socio-economic disparities in access to cardiac monitoring solutions.

In past work, we reported results stemming from large clinical studies where HealthKam AFib algorithms were trained and validated over the Android platform [15-18]. Results showed that the technology provides a reliable alternative to ECG and PPG devices under reasonably accepted operating condition.

In this work, we aim to assess the performance of the technology to measure HR and detect the presence of AF when operating in the iOS platform. As is typical in patient-centric applications, the training of algorithms requires considerable volumes of data while validation can be done with less data. Due to this data scarcity constraint, we attempt to validate performance on the iOS platform by making use the algorithms as trained on the Android platform. This approach allows us to conduct a smaller clinical study to just gather validation data. The results provided by such analysis represent suboptimal performance, since performance can be improved in the future by training the algorithms using more data captured on the iOS platform. The results also provide insight to the portability of the HealthKam AFib technology across platforms and future devices.

We collected validation data from 22 paroxysmal and persistent AF patients who did not participate in the training of the algorithms. Results in the form of *Bland-Altman* (BA) plots [20] demonstrate that 97% of estimated PR values have no more than 5 BPM deviation from reference HR captured by an FDA-approved ECG device. In addition, results in the form of *Receiver Operating Characteristic* (ROC) depict an *Area under the Curve* (AuC) of 0.93, a specificity of 0.88 and a sensitivity of 0.80 when detecting AF.

2. Methods

Validation data was collected from 22 paroxysmal and persistent AF patients who did not participate in the training of the algorithms. Table 1 presents the cohort statistics. The study protocol was implemented for all subjects in the same conditions and in accordance with the protocol description. The experiment was conducted in VPG Medical's facilities located in Rochester, (NY) after being approved by an *Internal Review Board* (IRB) committee.

Subjects participating in the study were spread across the entire skin-tone Fitzpatrick scale [19]. Measurements per subject were collected under 4 indoor illumination

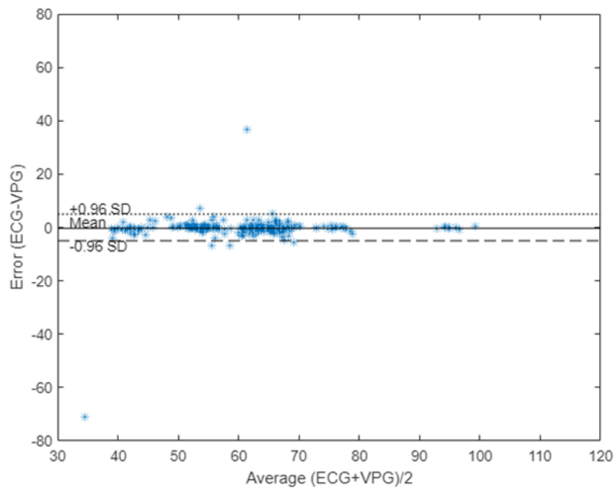

Figure 3: Bland-Altman plot assessing the agreement between video-based PR and reference HR.

levels (50, 100, 200, and 500 lux) and for 3 distances between the patient's face and the device (10, 20, 30 centimetres) for both LED and incandescent light sources.

The data were collected with HealthKam AFib installed on an iPhone 10, an ECG recorder (M5 ECG patch, Global Instrumentation, LLC, Manlius, NY, USA), the SPO2 finger PPG sensor (MightySat Rx, Massimo, Irvine, CA, USA), and a lux meter. In addition, we used an elliptical machine to increase the subjects' heart rate for a portion of the measurements.

Overall, we collected 958 recordings from the 22 AF patients (age: 67±10 years). 148 recordings were automatically discarded by our technology quality filtering algorithms due to subject motion and face obstruction. The remaining 810 recordings (85% of all recordings) were used as the validation data set. PR accuracy was assessed using BA analysis, and AF detection performance was assessed using RoC performance curve of sensitivity (SENS) vs. specificity (SPEC).

3. Results

The BA plot in Figure 3 presents the agreement between HR captured via the ECG patch and PR captured by HealthKam AFib. The plot shows unbiased estimation with strong agreement to ECG. 97% of estimated PR values have no more than 5 BPM deviation from the ECG HR measure.

The AF detection ROC curve in Figure 4 has an AuC of 0.93. Setting operating parameters like the S10 device results in SENS and SPEC of 0.96 and 0.5, respectively. The ROC curve implies that an optimal operating point for the iPhone X can be set to provide a SENS and SPEC of 0.88 and SPEC of 0.80.

The results in Figure 3 and Figure 4 demonstrate how HealthKam AFib trained on the Android Galaxy S10

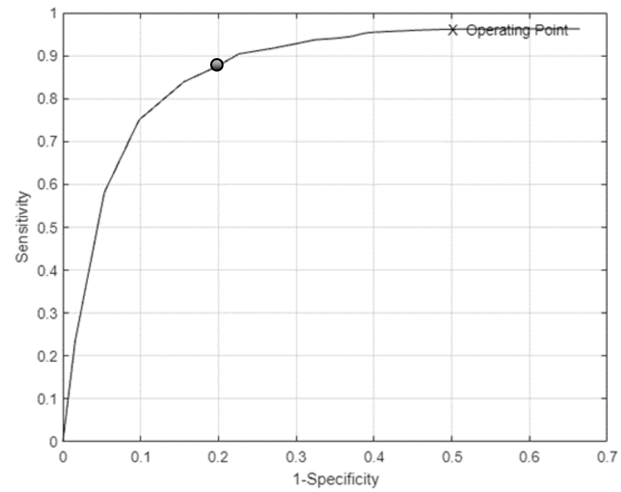

Figure 4: ROC curve assessing the accuracy of AF detection on iOS platforms. x represents the operating point using Android thresholds, while ● represents an alternative operating point.

platform ports well to the iOS iPhone X platform for measurement of PR. However, for acceptable AF detection, a different operating point along the ROC curve needs to be used.

4. Conclusion

The proposed video-based cardiac monitoring technology as implemented on the iOS platform enables accurate measures of HR and detection of AF under the expected range of indoor illumination levels, typical distances of the user from the device and across all human skin tone complexions. For HR detection, 97% of all measurements are expected to result in an error less than 5 BPM. More data is needed to further validate the alternative operating point providing better SENSE and SPEC of 0.88 and 0.8 respectively for AF detection.

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