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Cross-platform Remote Photoplethysmography (rPPG) based Heart's Vital Signs Monitoring

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Abstract — ***In the context of the COVID-19 outbreak, inexpensive technologies for assessing heart rate and oxygen saturation are critical for tracking symptoms and assisting in disease control. Methods for predicting heart rate and blood pressure (BP) without the use of sensor equipment have important applications in both the medical and computing fields. Smartphones are the most convenient device available to everyone today, and their cameras can be used to capture the relevant physiological data. The remote photoplethysmography (rPPG) technology can be used to measure heart rate (HR) and blood pressure (BP) utilizing videos of fingertip and real-time videos of the user taken with a smartphone camera or laptop camera. The PPG signals are collected by recording a videos from the smartphone camera while the users placing their fingers on the camera lens to extract required information. The signals then can be retrieved using minor variations in the video caused by changes in the skin's light reflection characteristics as blood flows through the finger as a result of cardiovascular activity. These color shifts are imperceptible to the naked eye, but digital cameras can detect them. It is feasible to obtain the camera-based PPG signal by covering a light source and the camera sensor with a finger. As a result, our system uses the camera and flash of a smartphone as the photosensor and light source, respectively. We run a series of tests to assess the PPG biometric trait's recognition performance, including cross-session scenarios. Statistical, curve widths, frequency domain, and fiducial points based characteristics are also considered. We used principal component analysis (PCA) to minimize the amount of frequency domain features and curve width groups, and then categorized them using the support vector machine algorithm. In order to estimate the health metrics, a cross-platform solution i.e. iOS application and Windows desktop application is developed.***

Keywords— **Heart rate measurement, Remote, non-contact, Camera-based, Photoplethysmography (PPG), Image Processing**

1. INTRODUCTION

According to the World Health Organization (WHO), heart disorders, such as heart attacks, strokes, heart failure, and heart valve abnormalities, are responsible for more than 30% of all fatalities worldwide. Because heart disorders can be asymptomatic and intermittent, especially in the early stages, clinicians have had a difficult time detecting them [1]. As a result, for outpatient use and daily activities, a basic cardiac rhythm monitoring technique (that is easily available and does not require extra electrodes/sensors) is required. As smartphones become more common around the world, and smartphone cardiovascular apps are developed and utilized to track users' health, the opportunity to supply high-quality smartphone cardiac monitoring technology to the medical community emerges.

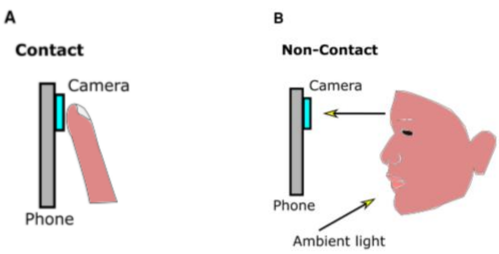

Fig. 1 describing methods for calculating blood pressure (BP).

(A) Contact methods - To obtain a finger blood volume pulse, you must touch your finger against the phone camera. Each frame averages the pixels in the video. A waveform as a function of time can be created by further processing and filtering the signal. To compute BP, features from the waveform are collected and fed into machine learning algorithms. The pulse transit time (PTT) can be linked to blood pressure (BP) [2], although many sensors are necessary.

(B) Non-contact method - Ambient light reflected from the face is used in non-contact procedures. The video is then processed to improve the signal-to-noise ratio of the hemoglobin signal, which is then sent into a machine learning algorithm to determine blood pressure (similar to contact methods). PTT [2] can be computed using only a

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single camera by measuring the difference between pulse arrivals at distinct body locations because several facial areas or body parts can be photographed at the same time.

2. RELATED WORK

The physiological foundations of PPG-based Heart Rate Monitoring are presented in this part, as well as several measuring methods and related study. Many previous research have shown that camera-based approaches can be used to remotely monitor cardiovascular activity without contacting the measurement location [3], [4]–[6]. In terms of the following aspects, camera-based vital sign monitoring systems outperform traditional methods: 1) The measurement is done without the use of any attached or wired sensors, and it is non-contact; 2) It does not necessitate the presence of trained personnel; 3) It allows for less intrusive, continuous monitoring for usage in a wider range of circumstances, as well as easier collection of rich, useful health-related data.

The camera-based health monitoring method has been tested in a number of settings, including ICUs, stressful work environments, the home environment, and space exploration. [6]. Ibrahim et. al. [4] developed an HR extraction approach based on blind source separation (BSS) from recorded videos. Photoplethysmography (PPG) is a technique for measuring blood volume changes in response to cardiac activity at specific body sites, such as the finger, earlobe, and face [5].

In hospitals, the PPG approach has been used to consistently assess SpO2 and HR. Recent PPG research has shown that with the right extraction techniques, PPG may be used to monitor BP [3], RR [4], and HRV [6]. As shown in Fig. 1, there are two types of PPG techniques now in use: transmission-mode PPG and reflectance-mode PPG. Figure 2 depicts a morphological representation of PPG coupled with the associated electrocardiogram (ECG). In the same way as ECG is a dependable method for monitoring heart activity, PPG has similar properties for prospective uses.

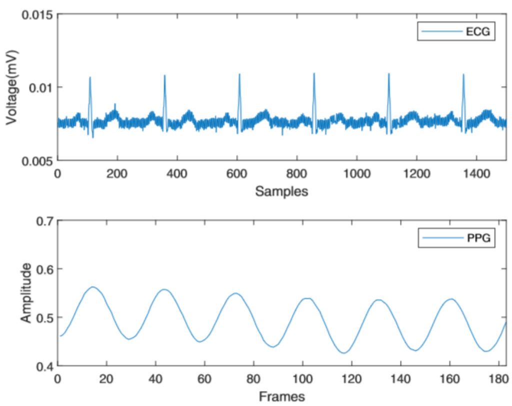

Fig 2. ECG and PPG morphological representation

3. PROPOSED SYSTEM & ALGORITHMS

We compute the mean of the pixel-wise luma component from the pixels in each video frame to get the signal from the raw video (see fig 4), so that if F is a video composed by a sequence of frames {f1,...,fm}, then the signal originating from F is:

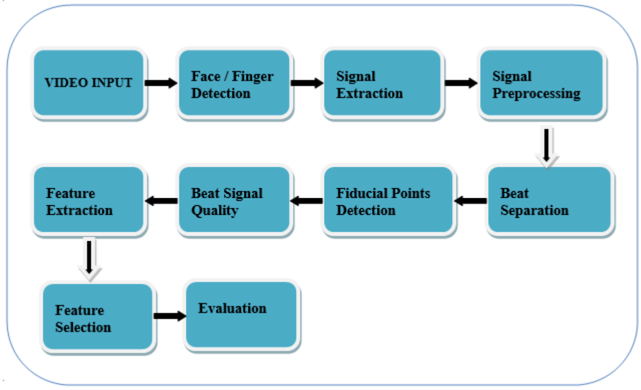

Fig. 3 PPG extraction to estimation processing flow

S = {Y (f1),...,Y (fm)}, where

$$Y(f) = \frac{1}{n} \sum_{i,j \in f} [0.299 f_{i,j}^{(r)} + 0.587 f_{i,j}^{(g)} + 0.114 f_{i,j}^{(b)}]. \quad (1)$$

In Equation 1, i and j iterate over the pixels of the image and the super scripts (r) indicate the considered RGB channel of the frame, either red green or blue. The channel coefficients of Equation 1 are taken from the ITU-R BT.601 standard.

Video Properties	Values
Frame width	360
Frame height	240
Data rate	1517kbps
Total bit rate	1517kbps
Frame rate	240 frames/sec

Table 1:- Input Video Properties

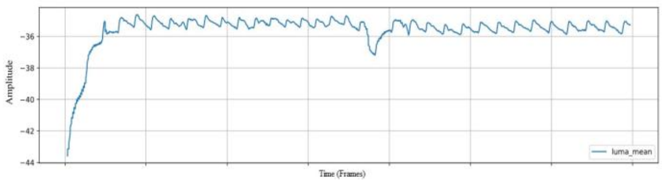

Fig 4. Mean of the pixel-wise luma component

Signal Preprocessing - We employ the following preprocessing methods to eliminate noise after extracting the signal from a video. To eliminate trends from the signal, we first compute and subtract the signal's rolling average from the signal itself. Slight hand or finger movements can often result in signal noise that bypasses our filtering system [8]. As a result, we create a set of individual beat quality criteria with the purpose of removing noisy beats from further processing. For the rolling average, we utilize a 1 second window size. Then, to reduce high-frequency noise, we employ a low-pass filter with a cutoff frequency of 4Hz (240 beats per minute) [4].

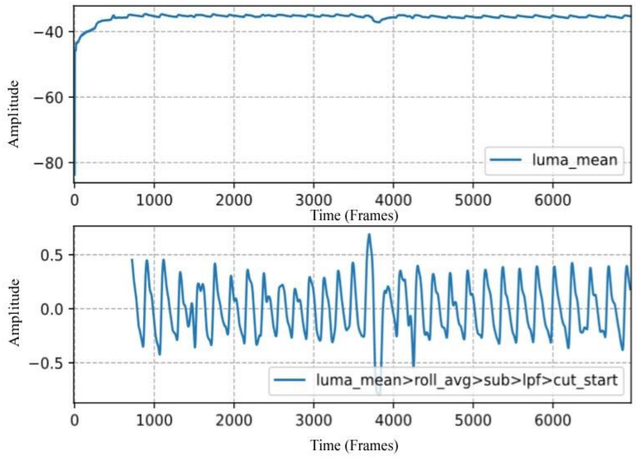

Fig 5. Signal Preprocessing – Rolling average

Fiducial Points Detection - Following the extraction of individual beats, we look for fiducial points in the signal to extract features.

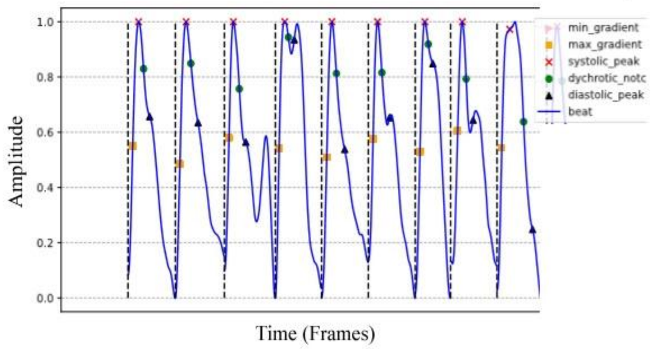

Fig 6. Fiducial Points Detection PPG signal

We pay special attention to three points: the systolic peak, the dichotic notch, and the diastolic peak. These points can be easily detected in low-noise signals by looking for maximums and minimums in the signal and its first derivative (see Figure 6 and 7). However, we discovered that this approach must account for noisy signals, so we created a more robust algorithm to detect them that relies on best guesses [8].

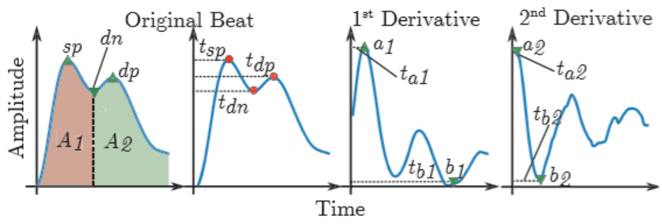

Fig 7. Fducial point based features

Feature Extraction - Statistical, curve widths, frequency domain, and fiducial points based characteristics are also considered. To make features independent of a user's bpm at the time of capture, we re-sample beats a fixed sampling rate of 1,000 Hz and normalize them so that the amplitude values sit in the same range as the physiological features [0, 1]. Features are calculated on a beat-by-beat basis, with each beat resulting in a sample.

To minimize the number of features in the frequency domain and the curve width groups, we apply principal component analysis (PCA) [1]. We fit a PCA with 100 components for the frequency features and keep only the first n components, which describe 99 percent of the space variance. We do the same thing with the curve width features, but we use a PCA model with 15 components. We discovered that the frequency group requires approximately 5 components (depending on the dataset), while the breadth group requires only 9. On the remaining features, we mix two alternative strategies for feature selection. We first compute the pairwise correlation coefficient between features, and then eliminate one feature from the data set at random if the correlation coefficient between them is rf1,f2 >.95 for a pair of feature distributions (f1,f2).

We stratified the data at random and trained two distinct classifiers, a support vector machine (SVM) with a radial basis function kernel and gradient boosted trees (GBT). Before feeding the data into the SVM classifier, we employ a conventional scaler to normalize it, and we only utilize the training part to fit the scaler.

It was confirmed that the rPPG obtained with the smartphone camera and display allows for better control of the emitted light, hence enhancing the acquired signal quality. In order to broaden scope and verify the results of proposed methodology the cross platform system is created to measure the heart rate and Blood pressure based on windows desktop application and iOS application for mobile user. The activity of building software products or services for several platforms or software environments is known as cross-platform development, which we have achieved by building same solution on different application environment like windows, iOS or Android.

4. DATA SETS & RESULTS

When employing an aggregate window size > 10, we discovered that single sample EER is above 15%, but quickly drops to less than 5%. We discovered that SVM outperforms the other models, with an EER of 1% at an aggregation window size of 20. Over the course of 4-5 capture sessions per user, we acquire a dataset of PPG readings from a group of 6 users. We create a data analysis pipeline and run a series of tests to assess recognition performance using a set of features collected from individual heartbeats.

In terms of heart rate measurement, our equipment performed admirably. In comparison to the present smartphone software, it was pretty accurate. We assumed linear regression in the case of blood pressure. This approximation, on the other hand, yields a promising result. Following table (Table 2) shows the actual heart rate, the heart rate measured with actual devices, and the heart rate assessed with the Instant Heart Rate application, all based on 10 samples.

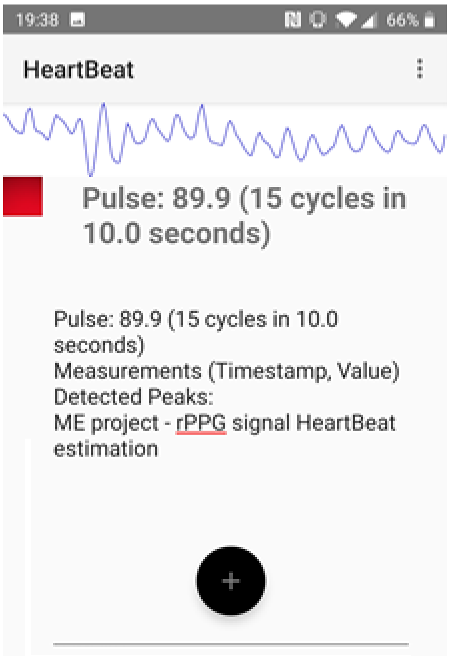

Fig 8. Measurement of Vital Signs on Smartphone

We discovered that when enough samples are gathered for a decision, we can attain identical error rates as low as 8%. Hence overall accuracy considering above methodology is 92 %.

Subject	Actual (device)				Measured (app)			
	a1	a2	a3	a4	m1	m2	m3	m4
1	88	82	80	85	88	86	85	88
2	82	80	78	75	80	80	78	79
3	73	77	74	85	73	78	74	80
4	88	87	85	75	88	87	82	75
5	106	101	100	98	106	102	100	98
6	72	67	74	80	72	67	74	80
7	75	79	80	74	75	79	80	74
8	89	93	91	99	89	93	91	99
9	92	88	87	94	92	88	87	94
10	76	77	79	73	78	77	76	73

Table 2:- Heart rate measurement with cross platform applications

5. CONCLUSION

In this paper, we present a method that uses a smartphone camera and a laptop camera to assess HR and BP using rPPG. In iOS framework, the rPPG signal is captured by recording a video from the camera while the user rests their finger on top of the lens, and in Windows, we used recorded videos to get measurements with a 92 percent accuracy. The signal is extracted based on subtle variations in the video caused by changes in the skin's light absorption characteristics as blood flows through the finger.

Future Work: We discovered that a number of parameters had a significant impact on signal fidelity. Initially, we discovered that the warmth of the fingertip alters blood flow, resulting in slightly varied measurements. Second, breathing has an impact on the signal: inhaling causes faster heartbeats than exhaling. We will have to consider these parameters to make any platform specific application to leverage the benefits of the methodology. Performance drops dramatically in the cross-session case samples which will also be considered as part of future work.

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