NTU Journal of Engineering and Technology (2024) 3 (2) : 10-20
DOI: https://doi.org/10.56286/ntujet.v3i2.788

IRAQI Academic Scientific Journals

P-ISSN: 2788-9971 E-ISSN: 2788-998X

NTU Journal of Engineering and Technology

Available online at: https://journals.ntu.edu.iq/index.php/NTU-JET/index

PPG-based Vital Signs Measurement Using SmartPhone Camera: Review

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Article Informations

Received: 03-12- 2023,
Revised: 09-04-2024,
Accepted: 23-06-2024,
Published online: 30-06-2024

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Key Words:
PhotoPlethysmoGraphy,
Smartphone Camera,
Heart Rate,
Blood Pressure,
Oxygen Saturation,
Respiratory Rate.

A B S T R A C T

Due to their growing popularity and rapid performance improvements, smartphones have the potential to be an accurate, low-cost physiological monitoring tool that is useful outside of the clinical setting. Since the cardiac pulse is responsible for the slight color changes in skin, a pulsatile signal that is also known as a photoplethysmographic (PPG) signal can be evaluated by utilizing a digital camera to record a video of your Region Of Interest (ROI).
This review Study focuses on several research works that used PPG-based video smartphone camera methods to measure Heart Rate (HR), Blood Pressure (BP), Oxygen Saturation (SpO2), and Respiratory Rate (RR). Comparing the approaches and results of each study (HR measurement studies produced acceptable findings with error rates less than 5%, BP error rates of results less than 10%, and SpO2 =<3.5%, by comparing the predicted models reading with the standard references reading) show how smartphone-based physiological monitoring might be used in medical settings.

Introduction

There is a need for affordable, user-friendly, accurate physiological monitoring systems that can be utilised in ambulatory or home environments. Smartphones are starting to be used, effective, and equipped with a range of sensors capable of gathering data from the external environment, processing the data instantly, and sending information over a distance using wireless correspondence. Due to these elements, smartphones are an excellent choice for a physiological monitor that can be "taken anywhere" without the requirement for more devices and their potential, has been investigated for numerous uses in medical telemonitoring applications.

A vital sign is a clinical measurement that indicates the state of a patient's essential body functions, according to the Oxford English Dictionary[1]. The four main vital signs that doctors and other healthcare professionals frequently monitor are Heart Rate (HR), Blood Pressure (BP), Respiratory Rate (RR), and Oxygen Saturation (SpO2). Information on the cardiovascular and respiratory systems can be found under vital signs. In clinical practice, contact-based technologies such as respiratory belts, finger pulse oximeters, Electrocardiogram (ECG) recorders, and sphygmomanometers regularly monitor these vital signs [2].

The cardiac cycle is a series of pressure changes that take place within the heart. Blood flows through various heart chambers and throughout the body as a result of these pressure variations. These pressure changes originate from electrical activity of heart which initiate from Sino Atrial (SA) node causing the Heart contract. This electrical activity is measured by using ECG [3, 4].

Photoplethysmography (PPG) is an optical method that measures minute variations in blood volume in the skin to determine factors related to cardio-respiratory function. Conventional PPG necessitates skin contact and is commonly utilised for pulse oximetry in the majority of pediatric healthcare settings. A version of this technology called camera-based PPG makes use of a camera to detect these variations in a subject blood volume in a contact and non-contact manner. The various benefits linked to non-contact ways of gathering patient physiological information have sparked interest in this technology[5].

In this study , the PPG Background was explained, the PPG-based video smartphone camera approaches for detecting HR, BP, RR, and SpO2 were covered. It also seeked to compare the approaches taken in each study with the outcomes that were eventually attained.

PPG Background

PPG is a low-cost, optical bio-monitoring technique and non-invasive described by Alrick Hertzman in 1937 (“plethysmo” means “fullness” in Greek) that has been used to detect the changes in blood volume at specific body regions during a cardiac cycle[6]. PPG is measured using a small light source and a photosensitive detector (photoelectric cell) applied to the skin. The tissue scatters and partially absorbs the light that is emitted. The photoelectric cell, which can be positioned close to or across from the light source (in the reflection or transmission modes, respectively), detects a portion of the scattered light that reemerges through the skin[7]. Figure 1. represents the Light-emitting diode (LED) and photodetector (PD) placement for transmission- and reflectance-mode PPG, respectively.

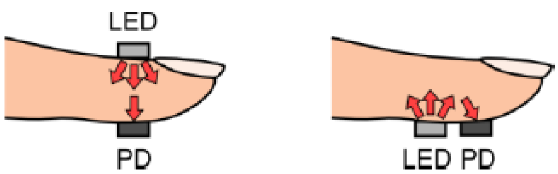

Figure 1. The LED and PD placement for transmission and reflectance-mode of PPG respectively [8]

Light absorption rises due to increase the blood flow to the skin surface capillaries during systole when the heart pumps blood to the body and the lungs. There is a reduction in blood volume in the capillaries and a decrease in light absorption as the blood returns to the heart via the venous network. The pulsatile (also called "AC") physiological waveform representing cardiac synchronised blood volume changes with each heartbeat is thus the measured PPG waveform. This waveform is overlaid on a much larger, slowly fluctuating quasi-static ("DC") baseline. Figure 2. Illustrates the changes in light attenuation produced by interaction with tissue. The DC component contains valuable information about respiration, venous flow, sympathetic nervous system activities and thermoregulation[9].

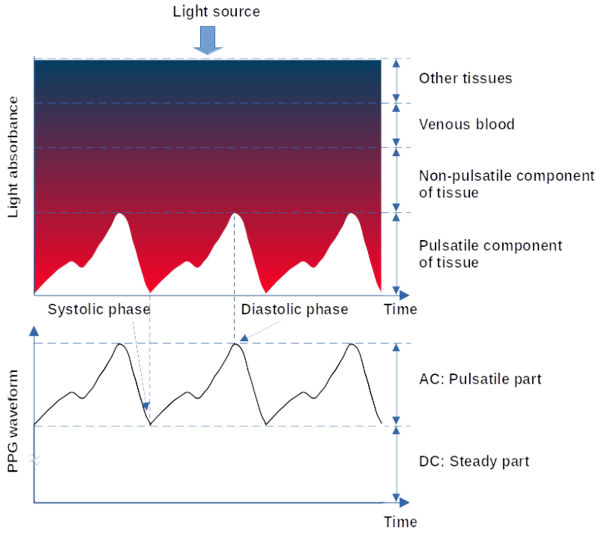

Figure 2. The variation in light attenuation is produced by interaction with tissue [9].

PPG Capturing with Mobile Camera

Because they are readily available and reasonably priced, smartphones provide a practical computer platform for point-of-care applications. Many people have smartphones worldwide, and this availability makes this tool attractive for medical diagnosis and physiological parameter estimation.

The video images recorded by the camera included light reflection information from the skin layer's surface and blood veins located on the hypodermic layer. On the other hand, the PPG signal is the result of measuring blood flow changes in one place, while the camera-based PPG signal is the result of averaging blood flow changes in the Region Of Interest (ROI) from a video image[10].

Smartphone-based PPG has the main advantage over established biometrics: the hardware requirements are low, and no specialised sensors are needed. This makes the technique even more suitable for low-cost feature phones [11]. Figure 3. Shows the mobile camera used for recording the PPG signal.

Good PPG signal quality depends on the skin area's properties, camera characteristics, LED usage, and light conditions.

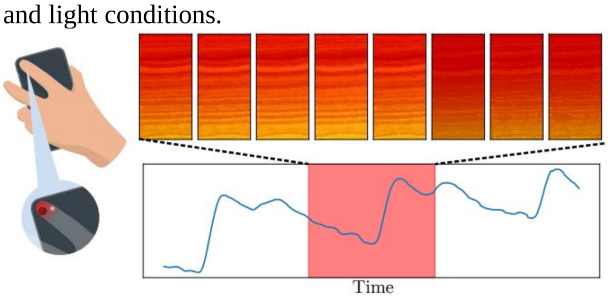

Figure 3. The mobile camera used for recording PPG signal[11]

Survey

1- HR

The number of cardiac contractions per minute is the HR, which represents the heartbeat rate (bpm). HR is a crucial determinant of a person's health. ECG signals provide the basis for the most precise HR tracking technique. As the cardiac rhythm periodically influences blood flow, inducing the periodical variation on PPG signals and both ECG and PPG signals are directly synchronised with the human cardiac cycle, The researchers proposed PPG signals-based smartphone camera to measure the HR. Some of the researchers used non-contact methods for measuring:

In 2012, Kwon *et al.* investigated the technique of measuring HR remotely through the use of facial video captured with a smartphone camera. First, a selfie video was taken with a smartphone's front facing camera. Using face detection, the facial region on each frame's image was identified, and the raw trace signal from the image's green channel was produced.. Independent Component Analysis (ICA) is applied to the raw trace signal to extract more accurate cardiac pulse signal. Frequency analysis of the ICA signal and the raw trace signal was used to obtain the HR. By comparing the estimated HR with the HR from the reference ECG signal, the estimated HR's accuracy was assessed. As a result of this study, an iPhone application for remote HR measurement (FaceBEAT) was developed[12].

In 2013, Yu *et al.* suggested measuring HR from the video using the Short-Time Fourier Transform (STFT). The video sequences of a subject cycling were processed using STFT to indicate the HR of the subject. The area between the eyes and the upper lip of the mouth in a video frame was chosen as the ROI. Because STFT can give more precise localised temporal and frequency information—particularly for the quickly changing HR pattern during an exercise routine—making it a preferred data collection method. Figure 4. Represent methodology used for HR estimation. The suggested method can yield a satisfactory outcome, according to experimental results, and the root mean square error (RMSE) for HR changes between 80 and 130 BPM is less than 2.5 BPM [13].

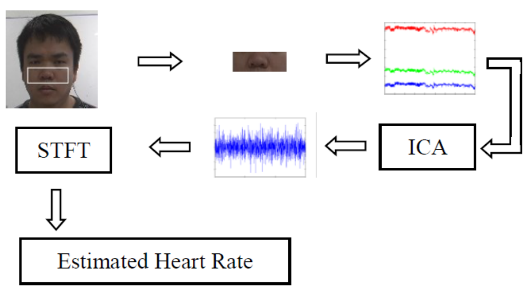

Figure 4. The methodology used for HR estimation [13]

In 2020 , Moya-Albor *et al.* described A non-contact HR estimate method utilising neural networks and vision-based techniques. This work highlighted the blood irrigation process of the heart pulse using a bio-inspired Eulerian motion magnification technique. The blood irrigation process was then inputted to a feed-forward neural network that has been trained to estimate the HR. The experimental analysis conducted by contrasting two magnification procedures—one based on Hermite decomposition and the other on Gaussian decomposition—over video recordings obtained from the wrists of five volunteers. The results demonstrated the robustness of the Hermite-based magnification method under noise analysis, with the worst-case scenario resulting in 4.24 bpm of root mean squared error. Additionally, the findings showed that the Hermite-based approach may be applied with a single Hermite and is competitive in the state-of-the-art (1.86 bpm in average of root mean squared error)[14].

Other researchers used contact method for monitoring HR:

In 2012, Lamonaca *et al.* proposed a study that addressed the accurate and dependable assessment of the Pulse Rate (PR) using a smartphone. The smartphone camera was utilised to assess the volumetric fluctuation of blood by tracking the variation in light absorption in the tissue. The method proposed in this study was organised into three logical phases: assessment of the correct smartphone use, system calibration, and PPG detection. Figure 5. Illustrates the block scheme of the suggested method to evaluate the PR. Following an assessment of proper functioning, the PPG signal was identified, and the PR was measured using statistical and adaptive analysis. The evaluated PR is compared with the clinically verified medical device Spacelabs 90207, an ambulatory BP monitor, to validate the approach given out. The experimental outcomes validated the accuracy and appropriateness of the suggested approach[15].

In 2013, Pal *et al.* presented a robust smartphone-based HR measurement system. The system required the user to place the tip of his/her index _finger on the lens of a smartphone camera while the flash was on. To mitigate the motion artifact issues, a two stage approach has been proposed. First, a finite state machine using multiple window STFT is used to detect the commencement of a good video signal. The HR is only calculated if an adequate and sufficient video feed has been received. According to the results, the noisy video signal was successfully recognised and rejected by the suggested strategy, preventing erroneous output. [16]. In the next year ,they presented a better way to use a smartphone for HR detection. By placing a finger on a smartphone's camera, a person's HR can be measured using reflective PPG. To improve performance while maintaining minimal complexity, they suggested using certain signal processing components. The accuracy of the solution is improved by the overlapping window-based technique. To identify erroneous signals and eliminate false positives, post processing components are employed in both the time and frequency domains. The findings showed that using the aforementioned components in addition to the usual spectral-based technique improves HR detection accuracy by over 50%[17].

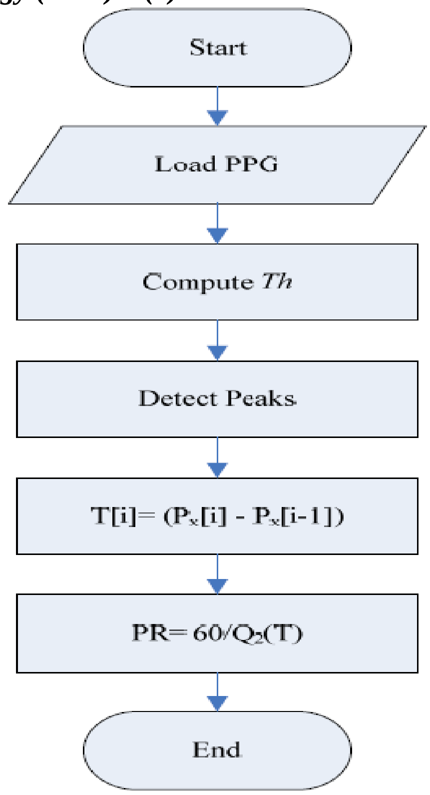

Figure 5. The block scheme of the suggested method to evaluate the PR [15]

In 2014, Lagido *et al.* proposed a study to use a smartphone camera for monitoring HR and rhythm in patients with heart failure. The phone camera was covered by the user's fingertip to obtain a PPG signal. Forty-three heart failure patients took part in the assessment. The following methodology procedures were employed in this study: signal filtering was made to enable more precise peak identification; PPG signal acquisition was calculated by adding up the number of pixels whose red component was above a given threshold. Consequently, a rectangular smoothing function was used. The signal captured by the smartphone camera for each patient had been compared to the ECG signal recorded in a hospital setting. The HR may be accurately calculated with an error rate of 4.75% when employing such approach, according to the results. Detection of atrial fibrillation was successful with a 75% sensitivity and 97% specificity[18].

In 2016, Lomaliza and Park illustrated a strategy for calculating HR using smartphone camera pictures of fingers. The three main components of the method were signal extraction based on region of interest, adaptive threshold system for signal noise reduction, and iterative outlier elimination strategy for cycle miss/duplication handling. Current approaches only function successfully on a limited number of devices and require high-speed processors to operate in real-time. On the other hand, the suggested approach operates reliably and accurately in real time on smartphones of all capacities. This is a crucial component since healthcare facilities need to be available to everyone, even those who cannot afford to purchase astronomically priced, high-performing smartphones[19].

In 2016, Siddiqui *et al.* presented an algorithm that employs PPG signals to estimate PR just utilising the smartphone camera as a sensor. Figure 6. Shows the flow chart of the proposed algorithm. When the results of the suggested technique were compared to the real PR, a maximum inaccuracy of three beats per minute was discovered. 1.98 % is the average error and 98.02 % is the average accuracy [20].

In 2016, Sukaphat *et al* introduced a program for the Android smartphone camera that records the light intensity from the fingertip blood volume. The camera had an LED flash. The PPG data was retrieved from each photo frame captured by smartphone using red channel of RGB signals. The Fast Fourier Transform (FFT) utilised to transform this contextual data into a time domain signal, which will then be employed in the HR estimated procedure. Figure 7. Represents the workflow of the pulse wave measurement system. The pulse rate recorded by the suggested system and a digital pressure monitor with a 0.57 percent error did not appear to differ significantly, according to the trial results performed by ten testers[21].

In 2017, Alafeef employed the method for HR monitoring via smartphones by using reflected mode PPG imaging of visible light. The method made use of the mobile phone's built-in camera capability, which records video from the subject's index fingertip. Using MATLAB 2014a software, a peak detection algorithm was used to locate the PPG signal peaks on the retrieved PPG data. After processing the video, The PPG signal resulting was used to calculate the subject’s HR. Figure 8. Illustrates the sequence of the procedure for HR estimation. Performance data from 19 participants was used to assess the system. The real HR was compared with the projected HR values that the suggested approach produced. The findings revealed a 99.7% accuracy rate and a maximum absolute error of 0.4 bpm, with the majority of absolute errors falling between 0.04 and 0.3 bpm [22].

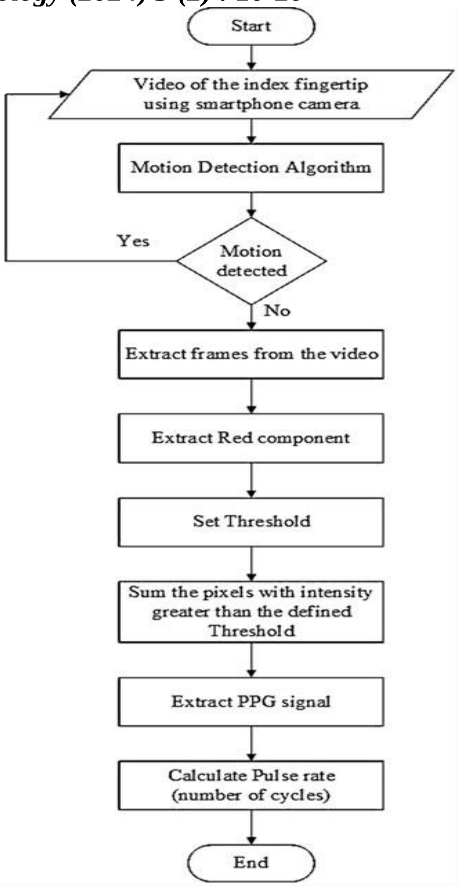

Figure 6. The flow chart of the proposed algorithm [20]

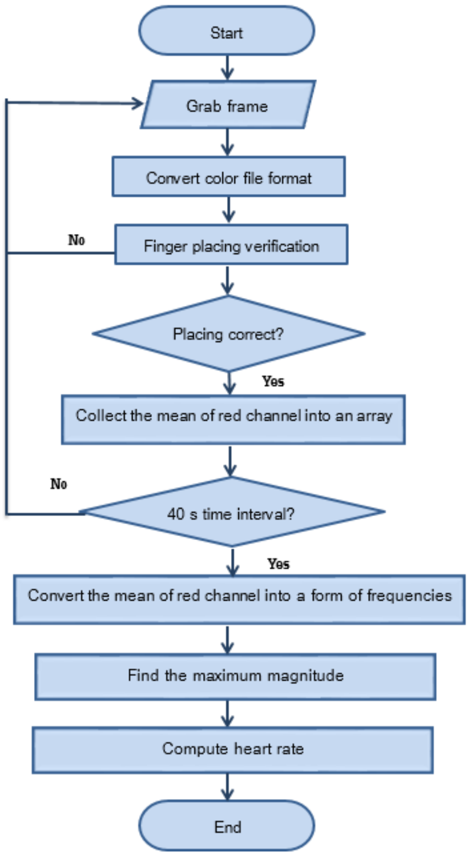

Figure 7. The workflow of the pulse wave measurement system[21]

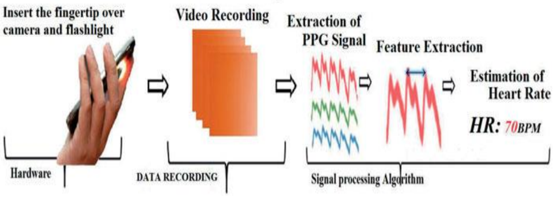

Figure 8. The sequence of the procedure for HR estimation [22]

In 2017, Hoan *et al.* proposed real-time HR measurement based on PPG using android smartphone camera. They created an Android application for real-time PPG signal processing and enhanced the method for extracting HR. Four hundred video samples captured by the Samsung smartphone camera are loaded into MATLAB for additional processing and algorithm evaluation.. A refined algorithm was created and evaluated on the Android platform using several Samsung smartphone models. The medical device Beurer BC08 was utilised as a reference device to evaluate the algorithm's performance. The 90% of samples with relative errors less than 5%, the Person correlation (r) of more than 0.9, and the standard estimated error of fewer than 5 bpm were among the accuracy measures they attained [23]. Figure 9. illustrates the Block diagram of PPG signal processing.

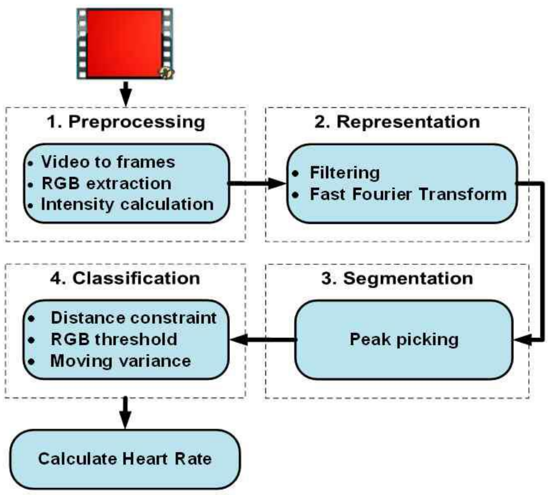

Figure 9. The block diagram of PPG signal processing [23]

In 2023, Yao *et al.* explained the method about extracting HR by using mobile phone video. When the finger video was recorded using the mobile phone's camera, the region of interest (ROI) was identified using an iterative threshold, and the pulse signal was derived based on changes in the ROI's grayscale resolution. The recovered pulse signal was then filtered to remove noise and interframes using a low-pass and high-pass Butterworth filter. To detect the pulse peaks and the HR resulting from the difference in pulse peaks, an enhanced adaptive peak extraction technique was finally suggested. The experimental results demonstrated that the HR extraction accuracy was affected by light intensity, frame rate, and resolution. The most obvious effect of light was seen in the average experiment accuracy, which reached 99.32% under ideal lighting conditions and only 72.23% under unfavorable lighting conditions. The accuracy increased by 0.9% when the frame rate was raised from 30 to 60 frames per second. The accuracy increased by 1.12% when the resolution was raised from 1080 pixels to 2160 pixels[24].

2- BP:

BP is a measuring of the force that the heart uses to pump blood around the body[25]. Close monitoring of BP is of great importance to detect and treat hypotension and hypertension early. Both, hypotension and hypertension can impair the function of vital organs, such as the brain, the heart, and the kidneys[26]. The maximum pressure exerted in the arteries during cardiac contraction is known as systolic BP, whereas the minimum pressure during cardiac relaxation is described as diastolic BP[27] .Many techniques used to measure the BP, recently the researchers depended on the relation between PPG signal and the BP to measure it using phone camera:

In 2014 , Banerjee *et al.* proposed a smartphone application that uses the Windkessel model to predict BP using PPG signals .A user's index fingertip video sequence captured by a smartphone camera is used to extract the PPG signal. In order to simulate atmospheric pressure, a set of time domain PPG features is utilised to estimate several lumped parameters of the Windkessel model. The program typically estimates systolic and diastolic BP values within a range of ±10% of the clinical measurement[28].

IN 2022, Zhang *et al.* designed non-Invasive BP measurement using a mobile phone Camera. They demonstrated a low-cost device that measures BP using a self-built convolutional neural network, a light source, and smartphone cameras. Thirty-four volunteers participated in the study. Following to-fold cross-validation, the model's mean absolute errors for both the systolic and diastolic BP were 4.44 mmHg and 3.68 mmHg, respectively. This means that the designed model satisfies the British Hypertension Society (BHS) Grade A standards and the Association for the Advancement of Medical Instrumentation (AAMI) standards[29].

3- SpO2

As there is a fixed quantity of hemoglobin circulating in the blood, the oxygen amount which carried in the blood is often stated in terms of how circulating hemoglobin saturated with oxygen. This is what is meant by ‘‘oxygen saturation level’’. If this is measured directly from an arterial blood sample, it is called the SaO2. If the measurement is calculated from a pulse oximeter it is called the SpO2[30].

In 2017, Bui *et al.* proposed a phone-based oxygen level estimate system dubbed PhO2. They made use of the camera and flashlight features. They proposed a set of techniques for spatial and spectral optical signal modulation together with an inexpensive add-on to optimise the optical signal of interest while minimising noise. Also, a feedback system and algorithm for light-based pressure detection are suggested in order to lessen the detrimental effects of human activity during the measurement. Additionally, they deduced a non-linear referencing model that enables PhO2 to calculate the oxygen content based on color intensity ratios captured by the smartphone's camera. Figure 10. Represents Overall system design and architecture of PhO2. An evaluation with six participants using a custom-built optical element on a COTS smartphone showed that PhO2 can estimate the oxygen saturation within 3.5% error rate when compared to standard pulse oximetry [31].

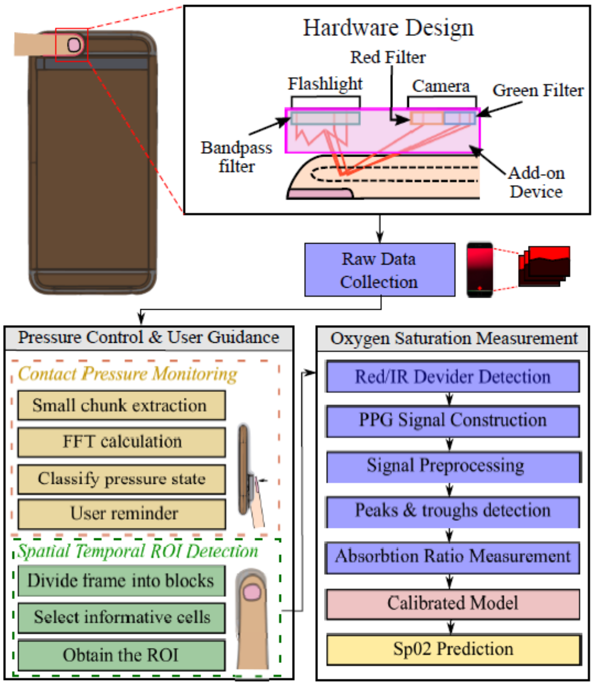

Figure 10. Suggested system for PhO2 monitoring [31]

In 2018, Ding *et al.* illustrated method for measuring SpO2 via smartphone camera using Convolutional Neural Networks(CNN). To mitigate motion artifacts, preprocessing techniques were utilised. A breath-holding exercise with 39 participants was utilised to assess the methods. Figure 11. Illustrates the block diagram of proposed methodology. They used two separate cell phones to compare the outcomes. The recommended model was compared to the ratio-of-ratios model, which is used in applications for medical pulse oximeters. The findings showed that the suggested method had a significantly lower mean absolute error from a medical pulse oximeter (2.02%) [32].

4- RR

RR is a vital sign with an underappreciated significance that can, in acute situations, prognosticate patients' mortality rate and need for invasive ventilation. It is the number of breaths you take per minute (BrPM). The normal respiratory rate for an adult at rest is 12 to 18 BrPM. Identifying abnormal breathing patterns can localise disorders within the respiratory system and help refine the differential diagnosis [33].

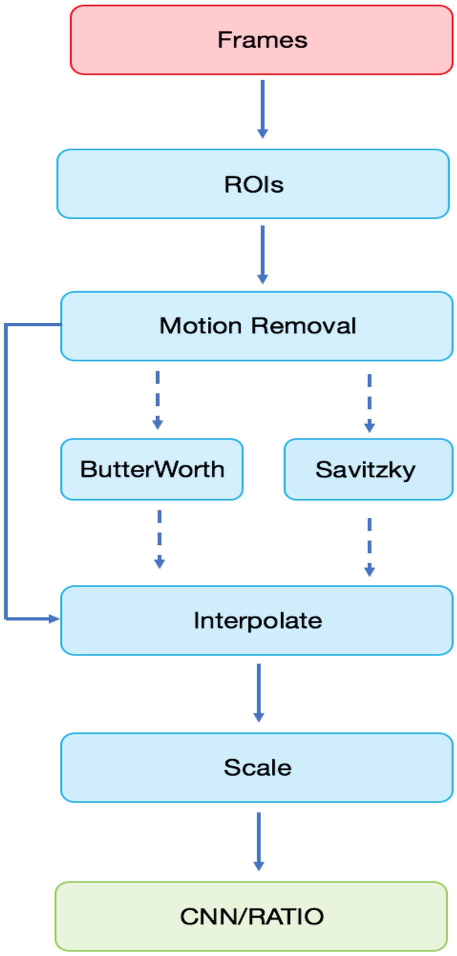

Figure 11. The block diagram of the proposed methodology [32]

In 2018, Sanyal and Nundy suggested an algorithm for RR and HR monitoring using facial video. They used Hue's reflected light to measure color variations to create a revolutionary image Photoplethesmogragh (iPPG) approach. Twenty-five healthy participants participated in the study. Two 20-second videos, one with the flash on and one without, were captured of each subject's face with little to no movement. They used a Biosync B-50DL Finger Heart Rate Monitor to measure HR and self-reporting to measure RR while the videos were being recorded. Figure 12. represent the flowchart of the suggested methodology. Compared to the Green channel, the suggested method of measuring iPPG using Hue (range 0-0.1) produced more accurate results. HR/Green (r=0.4916, p-value=11.60172, RMSE=0.9068) was less accurate than HR/Hue (range 0-0.1) (r=0.9201, p-value=4.1617, RMSE=0.8887). In contrast to RR/Green (r=0.3352, p-value=0.5608, RMSE=5.6885), RR/Hue (range 0-0.1) (r=0.6575, p-value=0.2885, RMSE=3.8884) was more accurate [34].

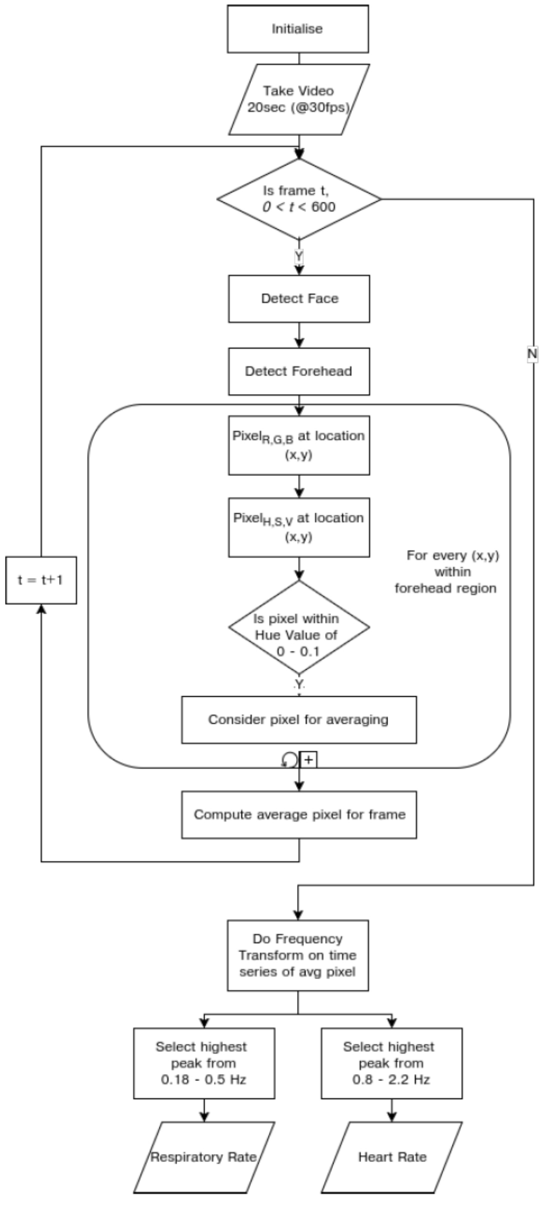

Figure 12. The flowchart of the suggested methodology [34]

In 2021, Hernandez-de *et al* suggested the method that used iPPG in the contact mode of a smartphone to estimate the instantaneous HR and RR values simultaneously. They contrasted the data from iPPG with specific biological sensors, such as the ECG and respiratory effort band. Five healthy subjects were evaluated using three different breathing strategies. The absolute mean errors of the instantaneous HR and RR computations were 0.94 ± 0.28 bpm and 0.40 ± 0.11 BrPM, respectively. The respiratory effort reference signal and the respiratory signal derived from iPPG showed a mean correlation index of 0.69 ± 0.14 [35].

Table 1: Summary of the Surveyed Researches

Participants	Number of volunteers & ROI	Vital Signs	Processing Technique	Accuracy of the procedure.
Kwon *et al.* [12]	- 10 subjects (8 males, 2 females) - Face(ROI)	HR	ICA & Frequency analysis.	error rates = 1.47% .
Yu *et al.* [13]	-area between the eyes and the upper lip of the mouth(ROI)	HR	ICA & STFT	RMS less than 2.5 bpm for HR variations between 80 bpm and 130 bpm
Moya-Albor *et al.*[14]	-5 subjects -Non Contact Wrist(ROI)	HR	-Feed-forward neural network - Hermite decomposition - Gaussian decomposition	1.86 bpm in average of root mean squared error
Lamonaca *et al.* [15]	- 10 subjects, from 27 to 60 years. - fingertip (ROI)	PR	Peak detection algorithm	-
Pal et al. [16]	-8 subjects. - fingertip (ROI)	HR	Finite state machine & multiple window STFT	-
Pal *et al.* [17]	- 33 subject (19 men and 14 women). - fingertip (ROI)	HR	-FFT for HR detection. -The accuracy of the solution is improved by the overlapping window-based technique. -To identify erroneous signals and eliminate false positives, post processing components are employed in both the time and frequency domains.	Accuracy : 50%
Lagido *et al.* [18]	- 43 subject with heart failure. - fingertip (ROI)	HR	--Motion detection algorithm -Threshold selection -Peak detection algorithm	error rate =4.75%.
Lomaliza and Park [19]	-5 subject (22-28 years) - fingertip (ROI)	HR	-Adaptive threshold system for signal noise reduction, and iterative outlier elimination strategy for cycle miss/duplication handling	error rate less than 5 % on currently available smartphones.
Siddiqui *et al.* [20]	-20 randomly selected subject. - fingertip (ROI)	PR	-Motion detection algorithm. -Threshold selection. -Peak detection algorithm.	Accuracy : 98.02 %.
Sukaphat *et al* [21]	-10 subjects - fingertip(ROI)	HR	-FFT	Error rate= 0.57
Alafeef [22]	- 19 subject - fingertip(ROI)	HR	A peak detection algorithm .	Accuracy :99.7%
Hoan *et al* [23]	-400 video samples	HR	-FFT -Peak detection algorithm .	Error rate less than 5%
Yao *et al.*[24]	-10 subjects (6 males and 4 females) - fingertip(ROI)	HR	Adaptive peak extraction technique.	Accuracy : 99.32%
Banerjee *et al.* [28]	- fingertip(ROI)	BP	Windkessel model & Artificial Neural Networks	Error: ±10% of the clinical measurement
Zhang *et al.* [29]	-34 subject	BP	CNN	Mean absolute errors for both the systolic and diastolic BP were 4.44 mmHg and 3.68 mmHg, respectively.
Bui et al.[31]	-6 subjects	SpO2	-FFT -Peak detection algorithm .	Error rate=3.5%
Ding et al.[32]	-39 subject	SpO2	CNN	Mean absolute error = 2.02%
Sanyal and Nundy[34]	-25 subject -face(ROI)	HR RR	Peak detection algorithm .	
Hernandez-de *et al*[35]	5 subjects	HR RR	-	Error rate for HR reached 0.94 ± 0.28 bpm and 0.40 ± 0.11 BrPM for respiratory rate.

Conclusion

In conclusion, this paper emphasised the potential of smartphone cameras as a practical instrument for physiological monitoring. The studies covered in the paper showed that it is feasible to measure SpO2, BP, HR and RR using a smartphone camera. To obtain the PPG signal(were the physiological parameter extracted from it), the researchers employed various techniques. Some researchers obtained a PPG signal by touching the smartphone camera with their finger, while other researchers utilised non-contact methods including using their wrist or face to collect the signal. Regarding processing methods, each study used a different approach, such as CNN, FFT, ICA and frequency analysis, feedforward neural networks, and so on.

All HR measurement studies produced acceptable findings with error rates less than 5%, BP error rates of results less than 10%, and SpO2 =<3.5%, by comparing the predicted models reading with the standard references reading. This opens up new possibilities for telemonitoring applications and increases accessibility to healthcare monitoring in daily life.

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