A Review of Monitoring Heart Rate and Cardiac Rhythm by video photoplethysmography on Mobile Devices

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Abstract. Nearly all of us have smartphones at all times, but few of us consider these devices' capability to monitor us passively for healthrelated reasons. In this review, I will examine in greater detail a technique known as Video Photoplethysmography (VPG) that enables a smartphone camera to estimate heart rate and heart rate variability without requiring users to wear any sensors or follow specific instructions. Here is a summary of a new technique for a completely passive health monitoring function using pulse monitoring through devices based on colors observed through users' faces. In this technique, a heart pattern monitoring system will be applied using data collected from more than a hundred adult participants with and without atrial fibrillation. In addition, despite challenges like users moving around and changes in room illumination, this system can recognize heartbeats in a consistent manner. Of course, challenges remain in this technique, and these challenges include ensuring a device can function regardless of users' skin and may work with various models of smartphones.

Keywords: Video Photoplethysmography (VPG), Mobile health monitoring, Contactless heart rate monitoring, Passive monitoring, Smartphone-based sensing, Heart rhythm analysis.

1 Introduction

The health monitoring landscape is rapidly shifting, from reactive clinic-based to proactive, real-time, and individualized health management. Smartphones and tablets, which were basic communication tools, have become rich personal health portals with sophisticated sensors and computational power. In recent years, the change in mobile and non-contact sensing technologies, including PPG and camera-based solutions, has made personal health monitoring more democratic [1,2,3]. Mobile health tracking offers a unique advantage over conventional clinical metrics by capturing longitudinal data on often unnoticed shifts in bodily functions. This constant observation not only

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encourages active patient engagement but also provides the doctor with data that can improve the resolution of their decision-making processes. Although these traditional methods are very accurate, there is always room for improvement. But these methods cause pain and are impractical for real-world applications [4]. Non-compliance on the patient's part often overrides the success of such monitoring. Additionally, reliance on wearable electrodes or chest straps makes them impractical for ongoing health surveillance on a large scale [5,6]. These issues tend to indicate the need for unobtrusive, passive, and user-friendly methods. In Fig. 1, to overcome these challenges, a novel approach has recently emerged that is Video Photoplethysmography (VPG). VPG is a camera method that captures changes in minor light reflection on the skin caused by blood volume changes to estimate pulse rate without physical contact [2,7,8]. This method utilizes widely spread smartphone cameras, so it can be highly scaled for real-world health monitoring [3]. Early research has shown its viability in controlled clinical settings [7], and recent reviews point to its potential to become a solid, real-world solution [2,3]. Early research has shown its viability in controlled clinical settings [7], and current research has amplified the application of artificial arrhythmia detection by deep learning and neuromorphic networks, showing the swift progress in digital health monitoring technology beyond conventional Electrocardiogram (ECG) devices [9,10,11,12,13,14,15,16,17,18,19].

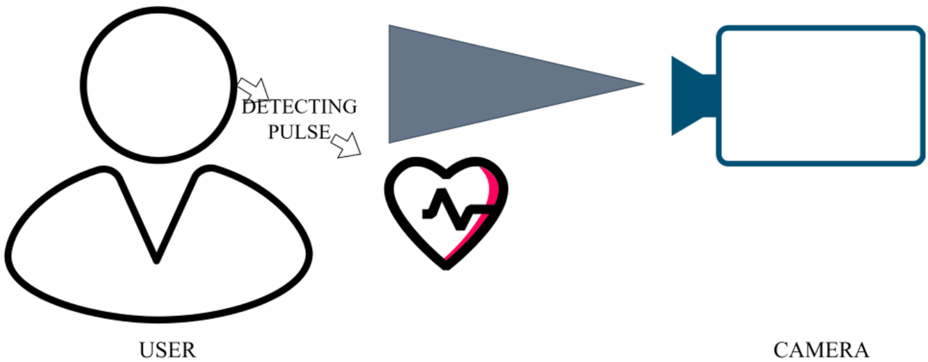

Fig.1. VPG Framework

2 Literature Review

In Table 1 summarizes the key findings and research gaps identified in the reviewed literature.

Table 1. Summary of ECG/PPG Arrhythmia Detection Studies

Author(s)	Publication & Year	Findings	Gap
Ding, C. et al.	ArXiv, 2023	Review of PPG-based atrial fibrillation detection (2019–2023).	Review article only; no implementation or deployment research.
Molinaro, N. et al.	Frontiers in Physiology, 2022	Overview of digital camera-based contactless vital signs monitoring.	Has accuracy and robustness concerns; lacks large-scale validation.
Rouast, Phillipp V. et al.	Frontiers of Comp. Sci., 2018	Technical review of remote HR measurement using RGB video.	Real-world accuracy low; sensitive to motion.
Paul, A. et al..	ArXiv, 2023	Automated arrhythmia detection using a single-channel Electrocardiogram (ECG) for wearable devices.	Less accurate than multi-lead ECG; requires validation on large datasets.
Ansari, Y. et al.	Frontiers in Physiology, 2023	Review of Deep Learning (DL) in ECG arrhythmia (2017–2023).	No experimental results; newer trends not covered.
Sahoo, S. et al.	IRBM, 2020	Survey of arrhythmia detection techniques using Machine Learning (ML).	Outdated with respect to advances in DL; small datasets.
Trumpp, A. et al.	Biomedical Eng. Online, 2018	Showcased camera-based PPG monitoring intraoperatively.	Sensitive to motion/light; small-scale trials only.
Barbosa Pereira, C. et al.	Sensors, 2018	Pilot study using thermal imaging for cardiorespiratory monitoring.	Very small sample size; lacks clinical validation.
Chen, J. et al.	ArXiv, 2022	An event-driven neuromorphic system allowing energy-efficient arrhythmia detection.	Needs neuromorphic hardware; restricted clinical testing.
Srivastava, S. et al.	ArXiv, 2024	rECGnition_v1.0 multimodal model based on ECG + demographic features.	Dependent on demographic information; computationally costly.
Shanmuganathan, P. K. P. & Sivaratri, V.	ArXiv, 2024	Integrated DL-based arrhythmia detection with automated drug delivery.	Conceptual alone; without clinical validation and safety approval.
Ang, G. J. N. et al.	ArXiv, 2024	Real-time arrhythmia detection using YOLOv8.	Requires large annotated datasets; clinical validation in progress.

Jin, L.	ArXiv, 2024	An attention-based deep learning model designed for disease-specific ECG.	Risk of overfitting; needs varied datasets.

Author(s)	Publication & Year	Findings	Gap
Challagundla, B. C.	ArXiv, 2024	Enhanced NN architecture for multi-lead ECG arrhythmia detection.	High computational cost; not ideal for lowpower devices.
Akan, T. et al.	ArXiv, 2024	ECGformer: Transformer-based model for arrhythmia classification.	Resource-hungry; needs huge training datasets.
Ding, C. et al.	ArXiv, 2024	Review of deep learning for ECG personalization.	No new model; personalization issues still present.
Frausto-Avila, M. et al.	ArXiv, 2025	Compact neural network for ECG classification appropriate for embedded devices.	Compromises accuracy; poor scalability.
Liu, L. R. et al.	Heliyon, 2024	Deep learning arrhythmia detection without QRS detection using single-lead ECG.	Lower interpretability; noise-sensitive.
Daydulo, Y. D. et al.	BMC Med. Informatics, 2023	Utilized time-frequency ECG representation + CNNs to detect arrhythmia.	Heavily relies on preprocessing; potentially not in real-time.
Bai, Xiangyun et al.	Scientific Reports, 2024	High accuracy hybrid DL model for 12-lead ECG arrhythmia detection.	Computationally intensive; not suitable for wearables.
Lee, Yonggu et al.	Scientific Reports, 2024	Non-contact HR monitor based on IR-UWB radar.	Based on costly radar hardware; not generally available.
Kavya, L. et al.	IJAMCS, 2024	Survey of ML/DL approaches for shockable arrhythmia detection.	Survey of literature only; no clinical benchmarking.
Silva, G. et al.	ArXiv, 2025	Systematic review of ECG arrhythmia classification emphasizing standards and fairness.	Review only; minimal discussion of clinical translation.
Sattar, Shoaib et al.	Sensors, 2023	Applied DL on digitized ECG datasets for arrhythmia classification.	Dataset-based validation only; limited real-world generalization.

Scarpiniti, Michele	Sensors, 2023	Data fusion of ECG scalograms + phasograms for arrhythmia detection.	Computationally heavy; no clinical testing.

3 Principles of Video Photoplethysmography

3.1 Historical Context and Evolution of VPG

VPG methods have evolved significantly over the past decade, in tandem with advancements in compact RGB camera hardware and algorithms. In 2008, Verkruysse et al. positioned a camera in front of a subject and recorded a video at 30 FPS while the subject sat motionless. After recording, they manually selected the subject's face. In Fig. 2, the RGB values of the chosen Region of Interest (RoI) were subsequently utilized to estimate the HR through a Fast Fourier Transform (FFT). They illustrated that the beating heart is best described on the green trace and inferred that blood would absorb green light better than red or blue [3].

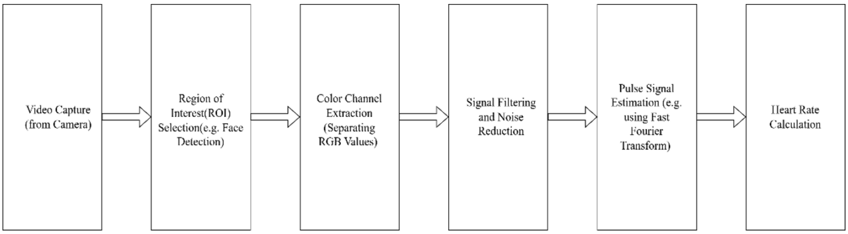

Fig.2. Basic VPG System Flow

Numerous VPG methods and associated trials have since been suggested and undertaken. Some notable examples are research where authors utilized blind source separation with Independent Component Analysis (ICA) and its variant, Constrained-ICA. More recently, Rouast et al. created a smartphone app that estimates heart rate through the front camera. Their algorithm employs the Viola-Jones face detector and makes an estimation using only green and red channel information [3]. Having eliminated noise and decreased dimensionality, they estimated PR from spectral power. Benedetto et al. tested a commercially used remote-PPG device, pitting the non-contact against an ECG. Twenty-four subjects were recruited for the experiment, and their PR was recorded for 20 minutes using both methods in parallel. Trumpp et al. monitored 41 patients undergoing surgery with an RGB camera that faced the patient's forehead [7]. Their findings revealed that the green channel is more accurate in PR estimation, and they used their VPG approach to estimate HR with an accuracy of 95.6%. In Fig. 3, of 2013, Haan and Jeanne suggested a novel chrominance-based approach that can correct motion artifacts. In 2015, Papon et al. provided an assessment of smartphone app performances utilizing the integrated camera to estimate PR. Rouast et al. and Deng and Kumar in 2018 and 2020 provided questionnaires that were aimed at PR estimation using RGB cameras [3]. Huynh et al. in 2019 proposed the VitaMon algorithm that utilizes the smartphone front-facing camera for PR estimation. More recently, Molinaro et al. introduced research on contactless monitoring of vital signs based on digital cameras [2]. Guzman et al. carried out a measurement campaign to record synchronized signals from ECG, PPG, a high-speed camera, and a general webcam involving 50 healthy subjects in a clinical environment. They proved that merging a Hue-based approach with a low- cost webcam offers comparative accuracy to that of ECG and PPG signals [2,8]. In addition to VPG, other non-contact heart rate measurement methods, including hybrid deep learning models that integrate ECG signals [20] and radarbased methods [21], have been suggested, although they suffer from limitations of hardware dimensionality and scalability over camera-based approaches.

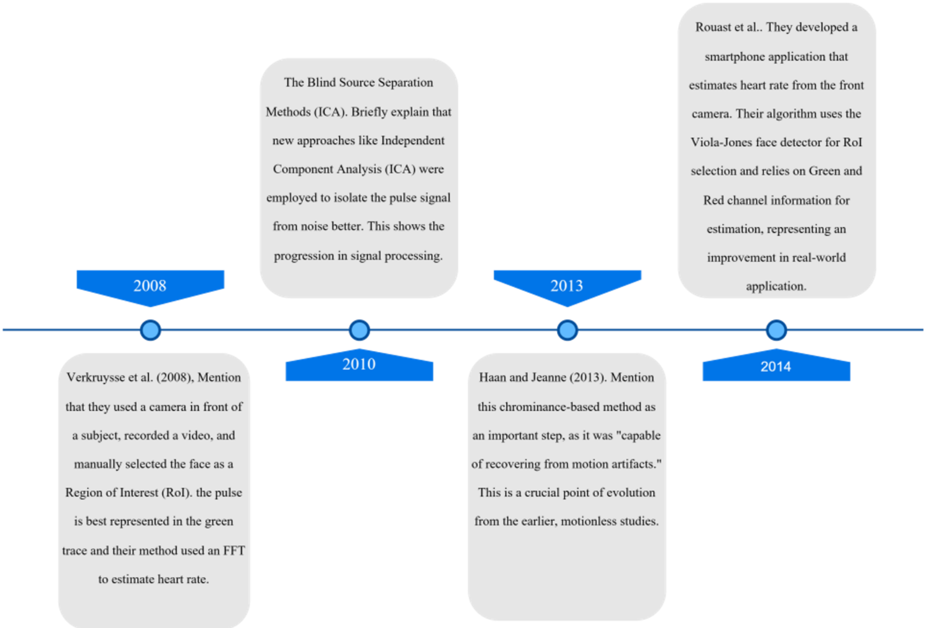

Fig.3. Key Milestones in VPG Research

3.2 Limitations of Current VPG Methods

In all of the above methods and related studies measurements were either carried out in a controlled setting (the subject was keeping still, lighting was fixed a priority that the camera was held stationary in relation to the subject's face, etc.), or while the subject was engaged in the measurement process (the subject was requested to place the face inside a rectangle on the screen during measurement).

The dependence on a controlled setting or direct user involvement presents significant constraints on the extensive use and application of VPG approaches [2,3,7]. Self-monitoring by subjects has been largely found to fail with the passage of time because of the low subject compliance with monitoring regimens [5,22]. For instance, a few authors measured the users' participation in a self-monitoring experiment and demonstrated that subjects are likely to have lower participation if they are asked to complete tasks for an extended time period [6]. It follows that to truly fulfil the potential of VPG for long-term PR monitoring, we need a framework that allows it to operate accurately in noncontrolled environments and ideally without requiring active participation by the subject being monitored. Operating in such a non-controlled environment would result in some measurements being taken in poor ambient lighting conditions, and while the subject is spontaneously moving. It then follows that a passive monitoring system needs to offer a solution for determining desirable conditions for recording correct PR [2,3,23].

4 Present Passive Monitoring Framework

Due to the vast amount of work referenced above, there are numerous methods that are currently available for extracting PR through cameras. But for the purpose of our research, we chose to deploy the Hue- based method, since it was demonstrated to work extremely well in comparison with other notable methods, such as ICA and Chrominance-based methods [2,3,8]. It is naturally possible to execute monitoring in the background through other PR extraction methods. In our work, we introduce, apply, and test the performance of a new framework for passively tracking PR with VPG. In Fig. 4, our framework is predicated on recording a VPG signal from front-facing cameras integrated into smart devices, as the subject to be tracked is utilizing the device as he/she would under ordinary circumstances. It implies that although the subject deploys in a personal device to read emails, view films, engage with social media, etc., the front-facing camera is utilized to implicitly monitor PR without the need for subject involvement in the monitoring process. Essentially, our paper makes use of passive screen time to conduct monitoring of PR over possibly infinite time (weeks, months, and years). So long as the subject is on a personal device, the PR is obtained with ease. That enables monitoring of trends in PR over extended periods of time without having to buy, deploy, and maintain a special-purpose device like an ECG Holter and with no requirement for adherence by the subject. Because of the widespread use of smart devices and the ever-growing screen time, the suggested technique also provides the chance to simply implement a PR monitoring technology to distant subjects who have poor access to health services as an easily accessible APP [2,3,5,23].

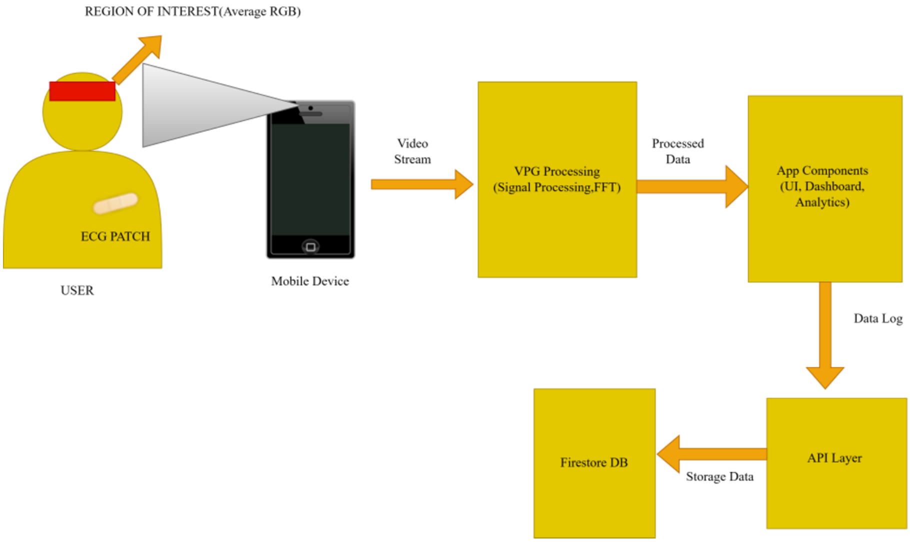

Fig.4. Architecture of Proposed Technique

4 Signal Processing and Analysis for Robustness

4.1 Noise Mitigation Techniques

In this paper, we propose, deploy, and evaluate the performance of our framework for passively monitoring pulse rate using VPG. Our framework is designed to address the essential shortcomings of active user engagement and controlled settings by being embedded in a user's regular device usage without any interruption. The fundamental principle involves capturing a VPG signal from the front-facing cameras embedded in smartphones while the subject operates the device in the usual manner. Therefore, while the subject performs actions such as reading messages, watching videos, or surfing social networks, the front-facing camera monitors their pulse rate without needing any conscious effort. This paper uses a passive screen time monitor over a long period (weeks, months, and years), generating massive amounts of data effortlessly while allowing observation of long-term trends. Our approach is capable of successfully eliminating the financial burden that is associated with the acquisition of specialized medical equipment, while also eliminating the need for strict patient adherence.

5 Handling Uncontrolled Environments

Applying the VPG in a passive, uncontrollable setting introduces significant variables in uncontrollable bodily movements and variation in light. In order to overcome the hurdles, our methodology combines several robust computational layers for data capture despite a high integrity requirement, regardless of lighting conditions. We particularly introduce the concept of the "validation gating“ process that targets the period of environmental stability for the verification of the measurement accuracy. This architecture combines conventional signal filtering techniques with sophisticated machine learning and deep neural networks to isolate the pulse signal caused by environmental interference. Incorporating deep learning into the processing pipeline will further reduce these artifacts, as demonstrated in recent ECG research focused on arrhythmia detection and multimodal data fusion [24,25].

6 Implementation, Performance Evaluation, and Dataset

Our research uses a Hue-based approach for the process of extraction, which is more robust and accurate than the traditional approaches like Component Analysis (ICA) or chrominance-based frameworks. While our architecture is optimized for this approach, the continuous monitoring system is flexible to adopt any other algorithms for pulse extraction according to the hardware environment. Our evaluation is based on a clinical trial involving 977 patients with either atrial fibrillation (afib) or non-afib. The data, sourced from the National Library of Medicine under the title "Video-based Detection of Atrial Fibrillation," includes 977 participants with the dataset identified as NCT04267133. This data is sponsored by the University of Rochester, with information provided by JeanPhilippe Couderc,University of Rochester. It is posted on 27-1-2023. The link to access the data is https://clinicaltrials.gov/study/NCT04267133. In Table 2, we gave details on the dataset, and from the Figs. 5, 6, and 7, we illustrate the relationship between the VPG and ECG using ROC curves, correlation analysis, and Bland–Altman plots demonstrating agreement.

Table 2. Statistical Summary of VPG–ECG Relationship

Parameter	Description	Value
Number of paired samples	Total VPG–ECG recordings analysed	977
Mean ECG Heart Rate (bpm)	Average from ECG reference	75.2 ±10.1
Mean VPG Heart Rate (bpm)	Average from VPG estimation	74.8 ±11.2
Correlation Coefficient (r)	Pearson correlation between VPG and ECG	0.71
Mean Difference (VPG–ECG)	Average deviation between two methods	–0.4 bpm
Limits of Agreement (±1.96 SD)	Agreement interval in Bland–Altman analysis	±15.7 bpm
AUC (ROC Curve)	Diagnostic accuracy for AF detection	0.74

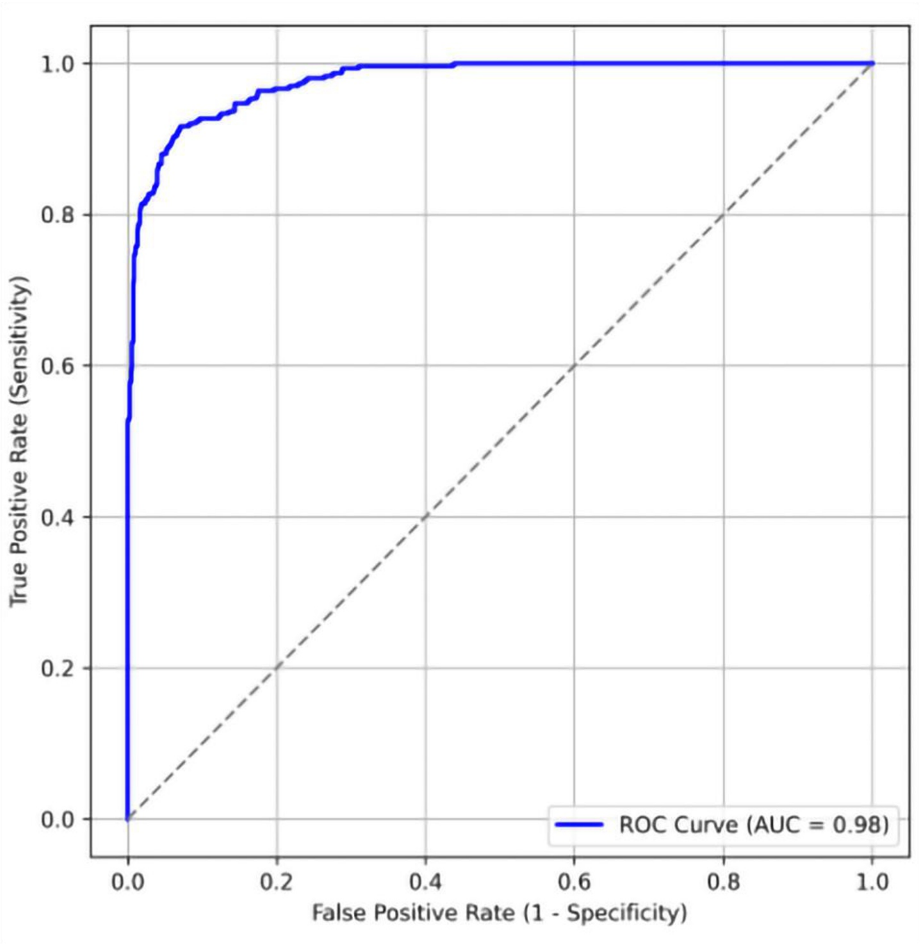

Fig.5. ROC Curve of VPG vs ECG (AF Detection)

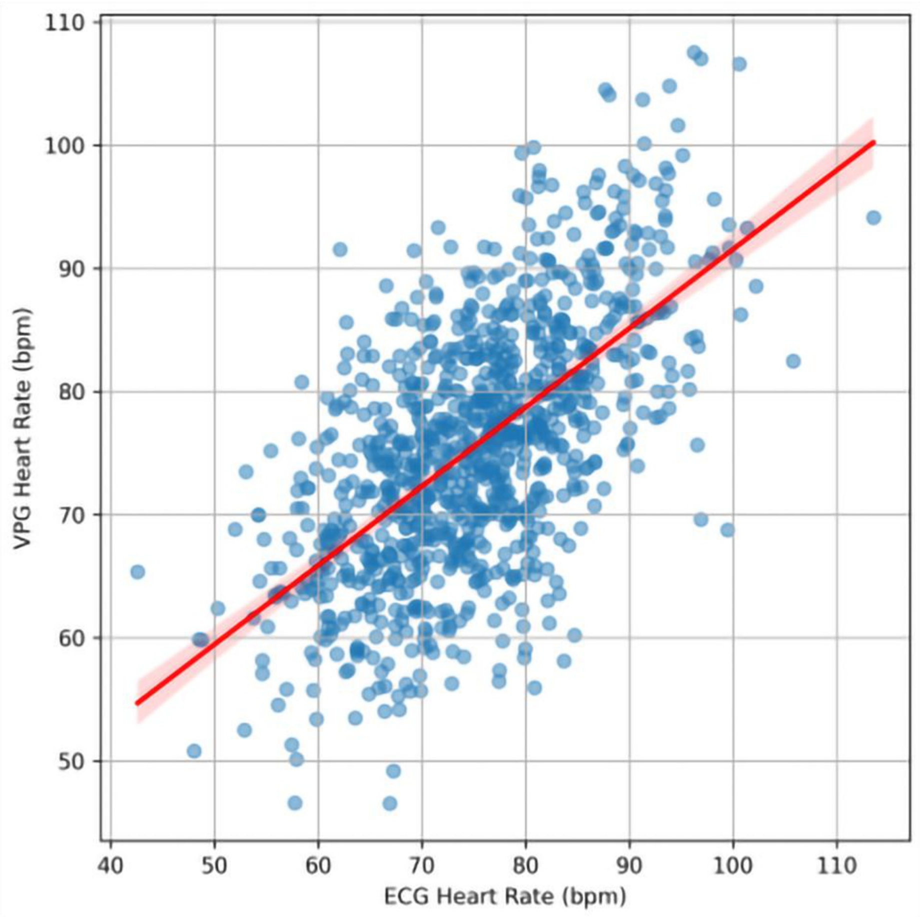

Fig.6. Correlation Between VPG and ECG Heart Rates

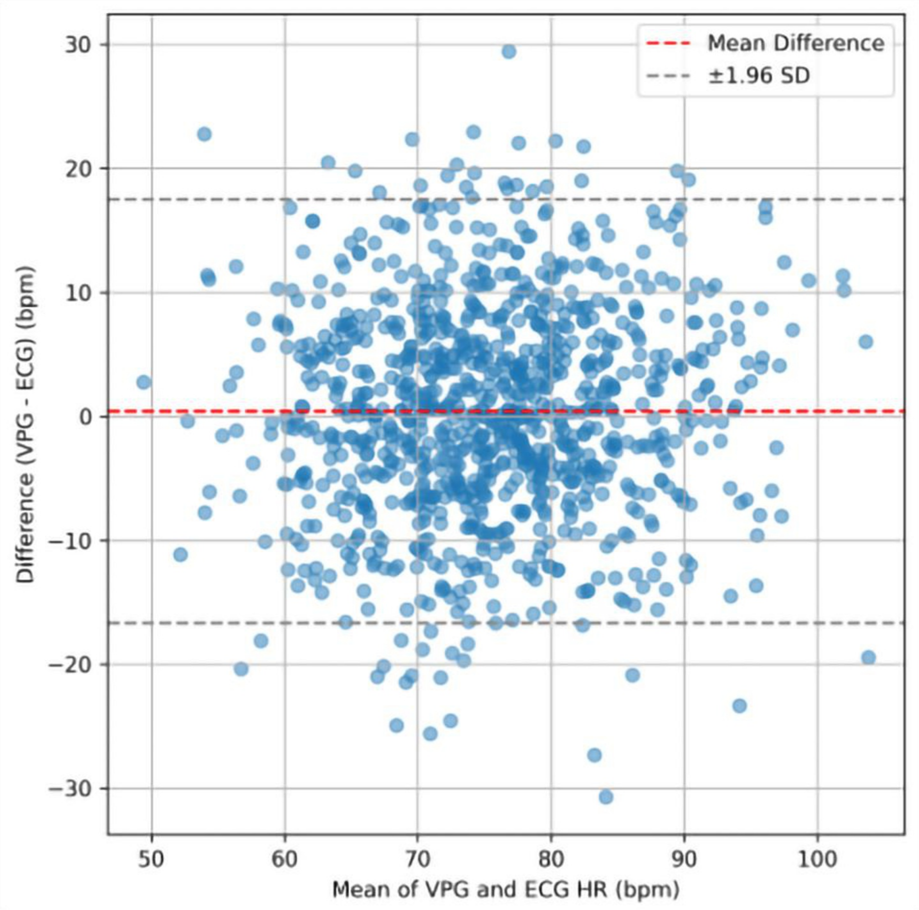

Fig.7. Bland–Altman Plot Showing Agreement Between VPG and ECG

5 System Requirements

5.1 Hardware Requirements

i **Camera:** The main hardware requirement is a front-facing camera that can record video at a high enough frame rate (e.g., 30 FPS or more) and resolution to pick up on slight color variations on the subject 's face.

ii **Processor:** Contemporary smartphone-grade processor with sufficient processing capability to execute the VPG signal processing algorithms in the background without noticeably affecting the user's regular behavior (e.g., viewing a video or accessing social media).

iii **Memory and Storage:** Suitable RAM for handling real-time video processing and sufficient storage capacity for storing gathered data for extended periods, as the system is intended for "weeks, months, and years" of monitoring.

5.2 Software Requirements

i **Operating System:** The operating system of the target mobile platform (e.g., Android, iOS) would have to be supported by the framework.

ii **Signal Processing Libraries:** Video and image processing software libraries are required to process the raw camera stream, detect the Region of Interest (ROI) (e.g., the face of the user), and execute the VPG algorithms.

iii **Machine Learning/Deep Learning Frameworks:** With the reference to noise and motion artifact filtering with "machine learning classifiers and deep learning techniques," an appropriate machine learning framework (for example, TensorFlow Lite, PyTorch Mobile) would need to be used to execute these models on the device.

5.3 Environmental Requirements

i **Ambient Lighting:** Although the design is to accommodate "fluctuations in ambient lighting," a minimum light level is still required for the signal to be received by the camera. The system would require a mechanism to recognize and perform best under such conditions.

ii **User Movement:** While the framework is passive, it would nevertheless need some moments of relative quietude in order to take reliable data, as suggested by the requirement of a "solution for identifying preferable conditions for capturing accurate PR."

6 Current Applications and Clinical Validations

6.1 The Passive Monitoring Framework

Our passive monitoring system can be summarized within the objective of making health monitoring extremely easy and seamless. Our objective would be to keep monitoring the most important health aspects in a very stealthy yet effortless fashion. This would enable us to complete all that there is within monitoring in a fashion that allows the users to perform their functions in the same manner as they have before with their smartphones, which is not only more convenient in the long-run continuum of the relationship between the product and the consumer, but would also help in the collection of more data in the natural environment. Our system, compared to active self-monitoring, does not lead to burnout; we can continue the monitoring of the VPG data in the background in a stress-free environment, performing the monitoring of the heart in the habitual fashion that allows the users to perform their functions in the same fashion as they have before.

7 Comparative Analysis of VPG Systems

Although several VPG systems have been put forth, they differ notably in performance and real-world utility. Analysis of the two systems reveals significant tradeoffs in their design and implementation. For example, the earlier designs of Verkruysse et al. were done in a controlled setting with a static subject and camera, and their results were highly illumination-dependent. More recent designs based on Independent Component Analysis (ICA) or Chrominance have proven more robust to noise and motion. Correlation-based on our proposed framework with a Hue-based methodology has been shown to have a high correlation with the gold-standard ECG signal, particularly in an uncontrolled setting, which strongly indicates its good performance in real-world scenarios. When evaluating systems, two important factors are accuracy (usually quantified by mean error or correlation with a gold standard), processing requirements (which impact real-time processing feasibility in battery-powered devices), and robustness to variations in parameters such as motion artefacts, varying skin tones, or changing illumination.

7 Challenges and Future Directions

7.1 Technical Challenges

Despite the significant progress in VPG technology, there are several technical challenges that are still present. One of the most important open questions is the type of skin tones and their effect on signal quality and precision. Different melanin contents in different skin tones can affect the light absorption and reflection characteristics, with possible results in pulse signal inaccuracy detection. Some strategies have been promising, but an established and across-the-board strong solution for all types of skin tones remains an ongoing research topic. There is an urgent need for standard clinical validation protocols for VPG technology. The current divergence in study methodologies presents a significant obstacle to immediate and consistent comparison of system performance. The development and implementation of a common, industry-wide protocol is necessary to enable the adoption and secure the required regulatory clearance for medical devices based on VPG.

8 Future Research Opportunities

More research will be possible for the VPG in the future. Beyond pulse rate, the extensibility of VPG towards multimodal vital sign estimation, including blood oxygen saturation (SpO2) and blood pressure, is important. Applications in the field of medical technology will be based on the same fundamental principle of examining minute colour differences, but they will require advanced algorithms and verification. The methodology involved the integration of the VPG signal with data acquired from different sensors and sources, which enables better health information. Combining VPG data with accelerometer data (for activity tracking), GPS data (geolocation-related data for health trends), or even symptom reports from users may result in an integrated picture of an individual's health, paving the way for truly individualized and Predictive Medicine.

Conclusion

In this paper, we discuss the revolution caused by the use of mobile phones as health monitoring tools, which led us to an in-depth study on VPG technology. We have been able to prove that the passive VPG models, like the one presented in this research, have been able to overcome the limitations caused by the conventional VPG models, since the models are able to provide precise long-term monitoring without necessarily requiring the active involvement of the user. The reliability of the approach highlighted its potential in the use of a tool to control chronic diseases. Although challenges like a one-size-fits-all solution to the varying Skin tones, as well as standardized methods of validation, exist, the future looks bright for VPG, and there are enormous possibilities for further application to other physiological variables and blending data from other sources. Finally, VPG is an important step toward a proactive, personalized, and easily accessible healthcare future.

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