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Research Article

Heart Rate Variation Analysis for Predicting Heart Conditions Using PPG and ECG Data: A Review

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ABSTRACT

An advanced optical methodology known as photoplethysmography(PPG) is employed to assess fluctuations in blood-volume within dermal tissues. Heart rate monitoring is commonly integrated into wearable devices. PPG's popularity derives from its cost effectiveness and convenience where continuous monitoring on the move is essential, such as in a disaster situation. PPG is prone to motion artifacts, though, which might skew the signals that are gathered. However, in comparison, the information that Electrocardiography (ECG) provides is the gold standard in tracking heart electrical activity — highly precise data on cardiac rhythm. ECG has a wide scope of applications in the clinical environment for the acquisition of heart rate and abnormality detection, to further elucidate details of cardiac performance. Autonomic control of the heart is a crucial indicator that is taken from PPG and ECG data and is used to show the Heart Rate Variability (HRV) or Phase I Workload status. The condition is fundamental in the diagnosis of heart problems, including hypertension, arrhythmias and cardiac diseases. This has led to the growing importance of analysis of HRV for early identification and prognosis of heart related health related issues. This review provides and compares HRV analysis using PPG and ECG for their predictive ability in the assessment of heart conditions. It then examines the properties of HRV data from both modalities informed by Signal Processing (SP) techniques to improve reliability. It reviews their contributions to improving the monitoring of heart conditions and to the more general landscape of HRV analysis in health care.

Keywords: Photoplethysmography(PPG), Electrocardiography (ECG), Heart rate variability (HRV), Pulse Rate variability (PRV), Signal Processing (SP).

1. Introduction:

Heart Rate Variability emerged as an important parameter not just for assessing the cardiovascular state but also for the operational status of the individual concerning the autonomic nervous system. An increase in the range of variability of the time intervals between heartbeats is indicative of enhanced adaptability, lower levels of stress, or stability in cardiovascular functioning as gauged by measurements of HRV. Additionally, several diseases including arrhythmias, hypertension, and cardiovascular death have also been correlated with abnormalities in HRV [1][2][29]. Over the years, the analysis of HRV has become essential for predicting cardiac disorders and both conditions of health and sickness. In recent times, studies on HRV have been highly intensified through electrocardiography and photoplethysmography. ECG, being the gold standard, measures the direct electrical activity of the heart, providing high-resolution heart rate data with exceptional sensitivity but the usage is very much constrained within controlled environments mainly due to its strict requirements for electrode placement [5][7][23]. On the other hand, PPG is a non-invasive optical technique for measuring blood volume changes under the skin, thus ideal for wearable technologies. It enables continuous and real-time monitoring of HRs in daily settings. However, PPG is more prone to motion artifacts and environmental noise that can easily degrade its accuracy when undertaking physical activities. Recent advances in signal processing and machine learning are enhancing the reliability of HRV assessments derived from PPG signals, further expanding its applications [12, 17, 24]. Both ECG and PPG offer complementary insights into HRV. ECG captures direct electrical signals from the heart, while PPG reflects peripheral blood flow changes which are directly affected by heart rate and vascular tone.

Combining these modalities raises the predictive accuracy of cardiac health assessments, and combined with advanced techniques such as deep learning for mental stress detection, hyperbaric HRV analysis, or topological feature learning using Graph Neural Networks (GNNs) [6][11][18]. Whereas clinical diagnostics is exclusively in the hands of ECG, PPG has revolutionized the notion of continuous, non-invasive monitoring through wearable devices. Strengths in both lend credence to the combined utilization of both settings-clinical and non-clinical settings-for a comprehensive approach towards analyzing HRV. This paper explores recent advancements in HRV analysis using ECG and PPG, highlighting how machine learning can address current limitations and discussing future opportunities to enhance HRV monitoring and cardiac health prediction [27][31].

2. Literature Review:

PPG is an invasive, low-cost method to determine the status of cardiovascular systems, including HRV, hypertension, and stress, which new developments in wears and signal processing improve its accuracy for continued and long-term monitoring. This variability in pulse rate measured by PPG is useful to understand the system. In application, it has proven useful in detecting variations otherwise hard to measure in wearables, in monitoring PRV during exercise through mobile and webcams [1] and also supplementing the estimation of HRV using a 1D CNN model based on wearable sensors for high-motion environments [2]. Indices of PPG related to reactivity in depressed subjects toward mental well-being and changes in ANS [3]. Due to recent works like models using machine learning algorithms that may provide improved accuracy and standardized measurements, measuring blood pressure using PPG is becoming of increasing interest as a cuffless substitute [4][15][18]. Some research has shown non-invasive glucose monitoring [5], while others are looking into the arterial stiffness and pulse wave velocity for diagnostics, AS and PWV [18]. More recently, PPG is applied in mental health monitoring. Deep learning supports fast stress and emotional state assessment using PPG and HRV analysis [10][13]. Wearable PPG smartwatches promote energy efficiency and accuracy by employing multi-wavelength illumination and signal compression for remote monitoring [7][11][25]. However, they also possess problems like motion artifacts, environmental noise, and sensor placement. As such, advances are already made to integrate PPG with other modalities, such as ballistocardiography, to enhance its usability under certain conditions [14]. ECG is the chosen method for HRV evaluation since it records cardiac activity directly but PPG is more suitable and adaptable for real-time usage and integration into wearables 9 14. Conclusion The applications of PPG include cardiology; there is more than that; it also manages to assess mental stress besides non-invasive glucose monitoring. Improve the robustness of the signals, standardize methods of calculation, and make these indices more applicable in health care.

3. Methodology:

Photoplethysmography (PPG) represents a noninvasive and economically feasible technique utilized for the evaluation of cardiovascular health, heart rate variability associated with hypertension, arterial stiffness (AS), and stress levels [3][5][8]. Notable advancements in wearable technologies and signal processing methodologies have significantly enhanced the precision of both short-term and continuous monitoring, facilitating accurate assessments of blood pressure and pulse rate [2][12][15]. It adapts to the resource-constrained environment by using mobile devices for monitoring HRV and to high-motion environments by deep learning like 1D CNNs [6][10][18]. It supports mental health monitoring, especially for stress and mood evaluations through autonomic reactivity and even blood pressure estimation with advanced features like higher-order derivatives [9][17][24]. PPG is used outside of cardiovascular applications, such as monitoring of blood glucose, mechanical alternans with video compression support for remote monitoring [19][25][29]. Signal noise and motion artifacts are still major concerns apart from sensor locations; multi-wavelength illumination and integration of ballistocardiography have been proposed to be utilized for better reliability [7][11][20]. PPG is near ECG accuracy with developments in machine learning and signal processing but has made efforts into signal robustness and standardized protocols for a much wider clinical application [1][14][26].

3.1. PPG Signal Acquisition

Photoplethysmography, or PPG, is an optical technique that measures the variation in blood volume within the peripheral vascular system [4][6][11]. It works on the principle of a light source, typically an LED, and a photodetector positioned on the skin. Light emitted from the LED travels through the skin, where increased blood volume in the underlying vessels either absorbs or reflects light back to the photodetector [8][10]. PPG captures the pulsatile part of blood flow, attributed to heartbeats, allowing for heart rate and HRV estimation [7][9][15]. The non-invasive nature and potential for continuous monitoring make PPG widely used in wearable devices like smartwatches and fitness trackers [3][5][16]. PPG sensors can be placed on different body parts, such as the wrists, earlobes, or fingertips, offering flexibility in ambulatory settings [12][13]. However, PPG signals are prone to interference from motion and ambient light, both of which can compromise signal quality. Signal processing techniques, including filtering and motion artifact reduction, are critical for reliable PPG-based HRV analysis [14][18][20].

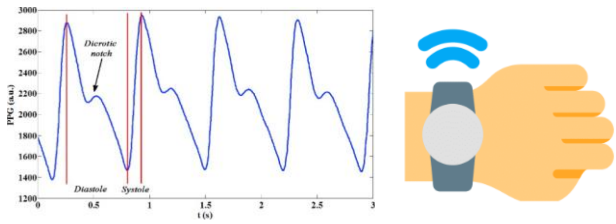

Fig. 1. Raw PPG signal

3.2. ECG Signal Acquisition

A traditional technique for recording electrical activity of the heart is electrocardiography (ECG), which involves the placement of electrodes on the skin to detect electrical impulses generated with each heartbeat, resulting from the depolarization and repolarization of cardiac muscles [1][3][7]. ECG produces a time-series signal representing heart activity over a period, which can utilize single-channel or multiple-channel systems, where electrode placement is optimized to capture electrical heart signals more accurately [2][9]. The HR and HRV information derived from ECG signals are highly accurate and widely used in clinical diagnostics for conditions such as arrhythmias, myocardial infarction, and other cardiac disorders [4][8][11]. While ECG remains one of the most reliable methods for obtaining HRV data, its use in ambulatory cardiac telemonitoring can be inconvenient compared to PPG due to the need for skin contact and precise electrode positioning [6][10][14]. Advances such as portable ECG devices and wearable ECG monitors have made it easier to collect high-quality data outside of hospital settings, thereby expanding the feasibility of continuous cardiac monitoring [5][12][15].

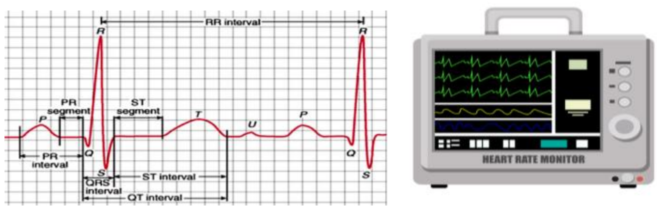

Fig. 2. Raw ECG signal

3.3. HR Estimation from PPG

Photoplethysmography (PPG) is a completely non-invasive technique that relies on detecting changes in blood volume within the microvascular bed of tissue [17][19][23]. Using an optical sensor, typically placed on peripheral body sites like the fingertip or wrist, PPG monitors blood flow changes by tracking variations in light absorption, which correlate closely with the cardiac cycle waveform. This allows for heart rate estimation by calculating the intervals between successive pulse peaks [16][21][24].

Pulse Interval Calculation: In PPG, the time interval between two consecutive peaks is termed the pulse interval, a key metric for determining heart rate (HR). Pulse interval reflects the temporal distance between pulse peaks, which is sequentially measured in the PPG waveform [18][22][25]:

$$PPI[i]=t[i+1]-t[i]$$

where t[i] is the time at which the i-th peak occurs.

Heart Rate Calculation: HR can be derived by taking the reciprocal of the average pulse interval (PPI) and converting it to beats per minute (BPM). Typically, this average PPI is computed over a brief period, such as 10 seconds, to maintain accuracy in HR estimation [20][26][27].

$$HR = \frac{60}{Average\ PPI}$$

Heart Rate Variability (HRV) from PPG: Beyond HR estimation, PPG signals are widely used to calculate HRV, which measures time-based variations between successive heartbeats and provides insights into autonomic nervous system (ANS) regulation. Common HRV metrics derived from PPG analysis include time-domain, frequency-domain, and nonlinear indices [22][28][30]:

- **SDNN** (Standard Deviation of Normal-to-Normal intervals):

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} (PPI[i] - \underline{PPI}\ )^{2}}$$

- **RMSSD** (Root Mean Square of Successive Differences):

$$\boldsymbol{RMSSD} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{N}-\mathbf{1}}\sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{N}-\mathbf{1}} (\boldsymbol{PPI}[\boldsymbol{i}+\mathbf{1}] - \boldsymbol{PPI}[\boldsymbol{i}])^{\mathbf{2}}}$$

The determination of heart rate from PPG offers a simple and effective approach for real-time cardiovascular monitoring. This process involves pulse interval detection, noise reduction, and the application of mathematical models to enhance HR accuracy. Additionally, analyzing HRV from PPG provides valuable insights into ANS function, supporting continuous health monitoring in both clinical and everyday settings [23][29][31].

3.4. HR Estimation from ECG

Heart rate (HR) is one of the more reliable measurements for ascertaining cardiovascular health using electrocardiography. [2][4][10]. ECG provides highly detailed information on the heart's electrical activity during each beat, with the R-peak being a crucial component of the ECG waveform, indicating ventricular contraction [3][5][12]. HR determination can be precisely performed by calculating the time intervals between successive R-peaks, known as R-R intervals, which measure the time between two consecutive heartbeats [6][9][13]. The HR determination process from ECG begins with signal acquisition, where electrodes placed on the skin record the heart's electrical activity over time. An electrocardiogram (ECG) signal is constructed from the P-wave, QRS complex, and T-wave, and the R-peak, positioned at the apex of the QRS complex, serves as the most outstanding feature for heart rate (HR) estimation. [8][14][15]. Several techniques are implemented in detecting the R-peak in order to correctly compute heart rate, starting from the Pan-Tompkins algorithm and transform-based wavelet techniques, which may be used to detect the R-peaks even when signals or data become noisy or altered. [7][11][16]. Once the R-peaks are identified, the next step is to determine the R-R interval, which is the time between two consecutive R-peaks. Since heart rate (HR) is inversely related to the R-R interval, this measure is used as an estimate for HR [4][7][12]. The HR can be mathematically calculated from the R-R interval using the formula:

$$HR = \frac{60}{Average\ R - R\ Interval\ (in\ seconds)} \text{ --}$$

This formula calculates the average R-R interval over a defined period, such as a 10-second window, resulting in HR measured in beats per minute (BPM). Averaging the R-R intervals over time helps to smooth out physiological fluctuations in HR, providing a more stable estimate [9][13][16]. R-R intervals can also be used to assess Heart Rate Variability (HRV), which reflects the time variation between successive heartbeats. HRV analysis gives insights into the activity of the autonomic nervous system (ANS), as it reflects the balance between sympathetic and parasympathetic influences on heart function [3][5][11]. Key HRV measures include the standard deviation of the normal-to-normal intervals (SDNN) and the root mean square of successive differences (RMSSD), both of which are essential metrics for evaluating the autonomic balance and cardiovascular health [6][8][14].

3.5. HRV Estimation:

Heart Rate Variability (HRV), a key metric for assessing the autonomic nervous system (ANS) and cardiovascular health, can be measured using ECG or PPG signals, depending on the application. ECG has been used in hyperbaric environments to analyze cardiovascular responses to pressure changes, with R-R intervals calculated for time and frequency-domain HRV metrics, confirming parasympathetic activity under higher pressures. A comparison with PPG-derived Pulse Rate Variability (PRV) validated PPG as a non-invasive alternative [1][3][5]. Meanwhile, deep learning methods, combining CNN-LSTM architectures, have enhanced PPG-based HR monitoring for wearable devices, achieving high accuracy in real-time settings with a mean absolute error of 6.02 BPM on the PPG-DaLiA dataset [4][6][7]. These approaches highlight the complementary roles of ECG and PPG in advancing cardiovascular health monitoring [8][14].

Paper	Algorithm	Signal	Preprocessing	Post Processing	Results
[1]	Graph Isomorphism Network (GIN)	Electrocardiogram (ECG)	Beat extraction, normalization, R-peak detection	None specified	Accuracies: 99.38% (NVG), 98.76% (HVG), 91.93% (QG-24)
[3]	POS	iPPG	Detrending	Peak Detection	High Agreement
[14]	Wavelet-based detection and frequency modulation model	ECG and PPG	Low-pass filtering, down-sampling, artifact detection	HRV and PRV analysis, estimation, oxygen saturation calculation	Characterized ANS response, increased respiratory rate with pressure, stable oxygen saturation
[12]	Deep Learning	PPG	Filtering	Classification	Accurate
[21]	NAS-PPG	PPG	FFT	Tuning	6.02 BPM

Table 1. HRV Estimation

3.6. Disease Diagnosis Using PPG:

PPG is another crucial non-invasive estimation of the cardiovascular state, particularly with smartwatches. It also provides an estimation of a rough measure of the change in blood volume along with an indication of heart rate and PRV. PRV is an indicator of activity in the autonomic nervous system and cardiovascular function; alterations are indicative of heart failure or stress-related pathology [9,19]. Medium PRV indices can be sampled at a lower rate of 50 Hz, optimized through selection of the fiducial point, for instance: the medium interpolate point for battery-efficient wearables [19][24]. Also, apex and up-slope optimized selection of the fiducial point enhances further the robustness of PRV when applied on different PPG morphologies and user conditions. Continuous wrist-PPG monitoring is applied for early diagnosis of hypertension and arrhythmia. The enforcement of long-term health monitoring compliance in any setting promotes its popularization. Development of signal processing of PPG in nonstationary conditions will facilitate its use in real time health-care and remote monitoring [7][10][13].

3.7. Disease Diagnosis Using ECG

One of the key apparatuses determining cardiac health is ECG, giving important information in understanding the way the heart functions, thus allowing the diagnosis in many disorders that involve the heart, including arrhythmias and myocardial infarction. However, due specifically to complexity and variability in heartbeat, ECG signal analysis is time-consuming by manual means. New developments of Graph Neural Networks, for instance, Graph Isomorphism Network, may lead to a new perspective in the automatic classification of ECG signals, and significant improvement has been done to improve the efficiency and accuracy toward the diagnosis of diseases. Three techniques, namely, NVG, HVG, and QG, are used on time-series ECG data transformed into graph representations in the article [1]. These changes allow the treatment of the ECG data as a network of interconnected points, with each technique extracting a distinctive feature of the ECG signal. The GIN model classifies the ECG graphs by iteratively updating each node's feature representation through neighborhood aggregation, thus being able to capture complex relationships in the data. The update rule for the nodes of GIN is:

$$h_v^{(k)} = MLP_k\left((1+\epsilon_k)h_n^{(k-1)} + \sum_{u\epsilon N(v)} h_u^{(k-1)}\right)$$

where $h_v^{(k)}$ is the feature vector of node v at the k-th iteration, N(v) represents the set of neighboring nodes, and ϵ_k is a learnable parameter. This update function enables GIN to iteratively refine each node's features, enhancing the model's ability to differentiate between healthy and abnormal ECG patterns. Experimental results also indicate that GNN-based methods could attain high classification accuracies on ECG data. In that, NVG achieved 99.38%, HVG reached 98.76%, and QG with 24 quantiles achieved 91.93%. Graph-based GNN approaches could hence be thought to be a reliable and efficient method for diagnosing cardiac conditions. This will imply that the techniques will be successful if GNNs are adopted as a vital instrument for clinical diagnosis and application to make healthcare professionals diagnose cardiovascular diseases with better accuracy, assuming further tuning is made [1].

4. Results:

The reviewed studies represent significant strides in physiological signal analysis and healthcare applications. Estimation models for blood pressure, such as those presented by Gupta et al. [17] and Byfield et al. [22], achieved high accuracy, with errors of −0.07 ± 4.47 mmHg for systolic BP and conformity to international standards like ESH-IP2 and BHS. HRV analysis highlighted the impact of preprocessing and tachogram length, as explored by Marzbanrad et al. [15] and Kajisa et al. [32], while genotype-specific T2DM variations were underlined in studies like Kamimura and Tamura [31]. The use of infrared PPG signals, as shown by Pelaez-Coca et al. [19], effectively reduced noise and improved accuracy when sampling rates were lowered. Wristwatch-type PPG sensors, developed by Lee et al. [28], demonstrated over 91% similarity with standard probes. Techniques such as PRV estimation from optical sensors, studied by Rodrigues et al. [16], exhibited high reliability, achieving 95% agreement with ECG-derived HRV. Furthermore, advanced graph-based methods for ECG classification, such as those proposed by Zeinalipour and Gori [1], achieved exceptional accuracies, often exceeding 99%. Features like the Poincaré plot and RMSSD, as used in Wang and Wu [12], delivered near-perfect accuracy in mental stress classification based on PPG signals. These findings underscore the potential of innovative algorithms, sensor designs, and data fusion approaches to advance non-invasive monitoring and personalized healthcare.

5. Discussion

Therefore, monitoring of heart rate variation and cardiovascular monitoring is quite challenging with PPG and ECG. Moreover, removal of motion artifacts is a severe task since accelerometer-based methods cannot deal with the fine movement like tapping wrist. Thus, gyroscopes or optical solutions will be required [3] [16]. Also, it seems that availability of limited datasets for healthy and CVD patients limits the generalizability of the algorithms which makes the need to acquire more data in both [22] [27]. Intensive methods don't have an application in real-time wearable technology. Lightweight methods provide alternatives that may be less complex but reasonably accurate [4][18]. Signal quality is a crucial criterion for dynamic activities and reliable PPG systems, as clinical validation standards are also important [7][21][26][30]. PPG with ECG may be promising to enhance monitoring but multimodal methods are still not very well-explored [14][24]. Monitoring over a long term through wearable electronics provides additional challenges like deformation of skin and perspiration which deteriorates signal quality; hence further research is warranted [11][17]. Further, resolution of the problems related to poor conditioning of sampling rates and fiducial point detection, which should be standardized to result in dependable findings, is required for the analysis of PRV data [10][13][20][25]. Fiducial point-based BP estimation algorithms have been adversely affected by the low quality of signals coming from physiological exercises and would have greater accuracy with higher-order derivatives of PPG [15][29]. Further perfect algorithms, appropriate signal processing, and clinical validation can further enhance PPG and ECG-based cardiovascular monitoring systems [12][31].

6. Conclusion:

This survey has increasingly revealed that integration of PPG and ECG can be of great benefit in cardiovascular monitoring, especially in case of HRV and initial signs of cardiac pathology. Real time and continuous monitoring has become more possible due to machine learning techniques incorporated in wearable devices though certain difficulties are noted and include Motion artifact removal and signal quality assessment, and developing machine learning algorithms that can be implemented on resource-limited devices. However, there remains a lack of clinical trials, inconsistent protocol regarding fiducial point identification, and a dearth of comprehensive datasets available to the public. Real-world, long-term assessments of the utility of PPG-based wearables, however, require different methodologies: longitudinal and model individual variations. Moreover, increasing the variety of acquired physiological signals to ECG and blood oxygen saturation will enhance the reliability and informativeness of such systems. In conclusion, significant efforts have been made to use PPG for cardiovascular monitoring as a replacement for conventional sensors; however, several issues need to be addressed in future research projects as mentioned above and defining a clinically proven and patient-oriented cardiovascular monitoring system that can be integrated using PPG data. These limitations can therefore be offset by PPG technology in offering better wearable health monitoring to cater for diverse people.

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