Photoplethysmogram (PPG) Signal Analysis for the Heart Rate Estimation using Shannon Entropy

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***Abstract*— a non-invasive optical technique called photoplethysmography (PPG) monitors variations in blood volume in peripheral tissues. It is frequently utilized in wearable technology and healthcare to track vital indications like heart rate, blood oxygen saturation, and vascular function. PPG measures the amount of light that is reflected or transmitted by the tissues by shining light into the skin. The variations in blood volume brought on by the cardiac cycle are what affect how much light is reflected or transmitted. It can be utilized in healthcare settings for early detection of cardiovascular diseases, monitoring of patient vital signs, and assessment of stress levels. Moreover, it can be integrated into wearable devices, enabling continuous HR monitoring in real-time for fitness tracking and personal well-being management.**

***Keywords*—** *PPG Signal, Heart rate, health monitoring, heart rate variability*

I. Introduction

Heart rate (HR) is a vital physiological parameter that provides valuable insights into an individual's cardiovascular health and overall well-being. Traditional methods for HR measurement, such as electrocardiography (ECG), have been widely used but require direct contact with the body and may limit continuous monitoring in daily life. In recent years, photoplethysmography (PPG) has emerged as a non-invasive and convenient alternative for HR analysis. PPG is a technique that measures blood volume changes in peripheral tissues using light-based sensors. It captures the variations in light absorption and reflection caused by the pulsatile blood flow during each cardiac cycle. PPG signals can be acquired using various devices, including pulse oximeters, wearable fitness trackers, and smartphones with integrated sensors, making it a practical and accessible technology for continuous HR monitoring in both clinical and everyday settings [1-2].

The analysis of HR from PPG signals involves extracting the temporal information related to cardiac activity and applying signal processing algorithms to derive meaningful HR estimates. The PPG signal provides valuable insights into the timing and intensity of each heartbeat, allowing for the calculation of HR in beats per minute (BPM) [2]. To estimate HR accurately, several key steps are involved in the analysis of PPG signals. These steps include signal pre-processing, peak detection, inter-beat interval (IBI) computation, HR estimation, and post processing techniques.

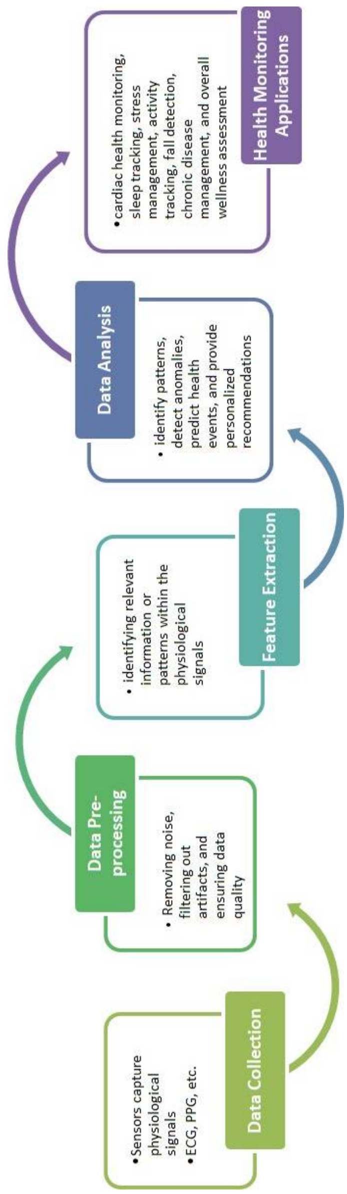

Fig.1 Overview of medical data analysis and applications

Signal pre-processing aims to enhance signal quality by removing noise, motion artefacts, and baseline drift. Peak detection algorithms identify the systolic peaks in the PPG signal, representing individual heartbeats. IBIs are calculated as the time intervals between consecutive peaks. HR estimation involves deriving HR values from the IBIs, either by computing the average IBI and taking its reciprocal or by employing advanced algorithms based on statistical analysis or frequency domain techniques as illustrated in fig. 1. Post processing techniques may be applied to further refine the HR estimates, such as outlier removal or smoothing algorithms.

The application of HR analysis using PPG has gained significant attention in various domains, including healthcare, sports, and wellness monitoring. In healthcare, PPG-based HR analysis has been integrated into wearable devices and remote monitoring systems to assess cardiac function, detect arrhythmias, and monitor stress levels. In sports and wellness monitoring, PPG-based HR analysis allows for real-time monitoring of exercise intensity, recovery status, and overall fitness levels.

However, challenges and limitations exist in HR analysis using PPG. Factors such as motion artifacts, sensor placement, physiological variations, and individual differences can impact the accuracy and reliability of HR estimation. Therefore, ongoing research is focused on developing robust signal processing techniques, calibration methods, and validation studies to improve the accuracy and applicability of PPG-based HR analysis.

In this field, recent advancements, methodologies, and applications of heart rate (HR) analysis using photoplethysmography (PPG) have made significant strides. By reviewing the current literature, we will highlight the strengths, limitations, and future directions within this rapidly evolving domain. Understanding these aspects of HR analysis with PPG will aid in the development of innovative healthcare technologies and enhance personalized monitoring and management of cardiovascular health.

Recent research has made significant strides in the field of heart rate (HR) and physiological monitoring, focusing on improving accuracy and usability of various methods and technologies. Dubey and colleagues [3] introduced a method to estimate HR from photoplethysmography (PPG) signals affected by motion artefacts, validated by simultaneously recorded ECG. Selvakumar et al. [4] employed Fast Fourier Transform (FFT) to recover respiration rates from amplitude variations in PPG signals, showcasing a robust approach for extracting vital signs. Dias and Silva highlighted the extensive capabilities of wearable health technology in monitoring various vital signs, including those for newborns and individuals in high-intensity scenarios.

Further research by Cunha [5] and Longmore et al. [6] addressed the variability in physiological measurements based on sensor placement, emphasizing the need for optimal sensor positioning to enhance data accuracy. Arunkumar and Bhaskar [7] demonstrated the effectiveness of a de-noising method for predicting HR across different physical activities, while Sharma et al. [8] achieved nearly 98% accuracy in HR measurement using a smartphone app. Ku et al. [9] explored PPG's potential for detecting additional physiological factors, such as respiratory rate and heart rate variability (HRV). Sharma [10] showed that HR values derived from PPG were reliable for shorter data segments, offering consistency across various patient conditions.

Biagetti and colleagues [11] analyzed the combined use of accelerometer and PPG signals in the presence of motion artefacts, providing insights into managing such challenges. Farhadi et al. [12] proposed a framework for wearable healthcare solutions that balances accuracy and computational efficiency. Loha et al. [13] identified 25 health problems and employed various methods, including machine learning, for PPG-based diagnostics. Falter et al. [14] evaluated the Apple Watch's HR measurement accuracy in cardiac patients, noting limitations in its use for this group.

Alfonso et al. [15] suggested a new methodology for synchronizing HR measurements across devices, improving the assessment of measurement agreement. Selvaraj et al. [16] found no significant difference in HRV characteristics between RR and PP interval methods, supporting the use of PPG for HRV analysis. Lewis and Short [17] reviewed non-invasive cardiac monitoring techniques and their variations during exercise and recovery. Thomson et al. [18] compared HR measurements from Fitbit Charge HR2 and Apple Watch with ECG, noting decreased accuracy during high-intensity exercise. Taylor and Lipsitz [19] covered various methods for HR analysis using physiological signals. Periyasamy et al. [20] surveyed algorithms for estimating HR from PPG and accelerometer signals in physical activity, while Düking et al. [21] discussed the limitations of statistical methods in evaluating wearable devices' reliability. Finally, Lee and Gorelick [22] assessed the Smart-health watch's performance, noting its reliability in controlled settings but limitations during significant body movement.

Overall, these studies reflect a broad range of approaches and technologies aimed at enhancing HR and physiological monitoring, each contributing to the advancement of wearable health technologies and their applications.

II. Analysis of Wearable Data: Methodology

Wearable technology supports in the continuous monitoring of patients, enhances the management of chronic illnesses, reduces health care expenses, prevents emergencies, and raises the standard of healthcare. With a goal to increase data analytics for research purposes, the devices have a lot of potential to provide healthcare data [23]. Analysis is challenging because to a lack of user experience and feedback, poor user involvement, privacy concerns, and data security challenges, among other things [24].

A. Cardiac Health monitoring using Wearable

Cardiovascular disease risk can be predicted using measurements of heart rate (HR) both at rest and during activity. A high resting heart rate has been linked to an increased risk of coronary artery disease and all-cause mortality in healthy populations. It has also long been known to be a risk factor for poor outcomes in heart failure patients. Increased acute cardiovascular events are associated with impaired HR recovery post exercise. In healthy persons and in patients with heart failure who have a lower cardiovascular risk, HR variability (HRV) has also been shown to be significantly associated with the risk of adverse cardiovascular events. In the design context of wearable system, a simple structure that represents the flow of monitoring cardiac health using a wearable watch:

- *Heart Rate Measurement*: The wearable watch measures the heart rate using sensors, such as optical sensors or electrocardiogram (ECG) sensors.
- *Data Storage*: The heart rate data is stored in the memory of the wearable watch.
- *Sync with App/Dashboard*: The watch periodically syncs with a smartphone app via Bluetooth or other means.
- *Data Analysis*: The app analyses the heart rate data and displays it in a user-friendly format.
- *Abnormal Heart Rate Detection*: If the app detects an abnormal heart rate, it sends a notification to the user.
- *Notification*: The user receives a notification on their smartphone app.
- *Action*: Based on the notification, the user can take necessary actions, such as seeking medical attention.

A high-level representation of the flow and the actual implementation may have more complex details. Commercial wearable assess HR and heart rhythm using ECG or PPG signals through analysing beat-to-beat time intervals and employing algorithms to recognize heart rhythm. The gold standard for measuring HR and cardiac rhythm is an ECG sensor, which comes in a variety of shapes and sizes. The clinical acceptance of data and its analysis through wearable like watches or wristbands, as well as other commercial devices, present significant challenges in this context [25-28].

B. Proposed Method: Shannon Entropy based HR estimation

In this paper, Shannon entropy can be utilized as a criterion to identify significant peaks in a signal. Here's an approach for using Shannon entropy for peak detection is summarized and illustrated in fig. 2:

- *Preprocess the signal*: If your signal is noisy or contains irrelevant information, it's beneficial to preprocess it before applying peak detection. Common techniques include noise reduction, filtering, and baseline correction.
- *Define a window*: Select a window size that determines the local neighborhood around each data point. The window size depends on the characteristics of your signal and the expected width of the peaks. It should be large enough to capture the peak and its surrounding information.
- *Compute the probability distribution*: Calculate the probability distribution within each window. This involves dividing the window into smaller bins or intervals and determining the probability of the signal falling within each bin. You can use histogram- based techniques or kernel density estimation for this step.
- *Compute Shannon entropy*: Apply the Shannon entropy formula to the probability distribution obtained in the previous step. Shannon entropy is given by:

$$H = -\sum p(\mathrm{i}) log2(p(\mathrm{i}))$$

  Where, $p(\mathrm{i})$ represent the probability of the signal falling within the i-th coefficients [29].
- Set a threshold: Determine a threshold value for the entropy that distinguishes between peaks and non-peaks. Peaks typically have higher entropy values compared to the background or noise. You can either select a fixed threshold based on prior knowledge or dynamically estimate it using statistical methods.
- Detect peaks: Identify the positions in the signal where the entropy exceeds the threshold. These positions correspond to the significant peaks in the signal.

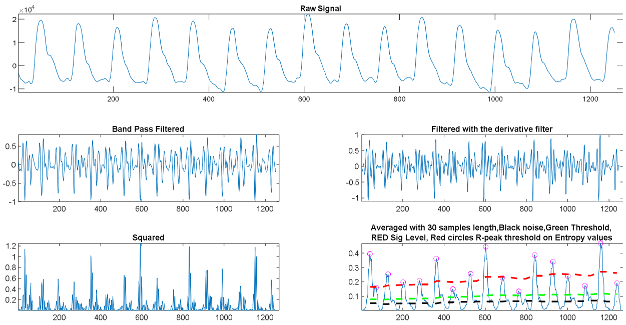

Fig. 2: Waveform for the Shannon based peak-detection

III. Results and Discussion

In this paper, a review study carried for the cardiac health monitoring as summarized in the Table.1 based on PPG signals using the wearable like digital/commercial watches in the rest and physical active conditions. The heart rate (HR) data from a digital watch typically includes the following information/parameters:

- Beats per minute (BPM) indicate the number of times the heart beats in a minute.
- Heart rate variability (HRV) is the variation in time between consecutive heart beats, usually expressed in milliseconds.
- Resting Heart Rate analysis indicate the heart rate when the person is in a state of rest.
- Active Heart Rate analysis indicates heart rate when the person is in a state of physical activity.
- Trends represent the direction of change in heart rate over time (e.g., increasing, decreasing, and stable).

These parameters are very essential for the cardiac health condition monitoring using the wearable. However, to compare the feasibility of HR analysis with respect to ECG signal interpretation BPM is enough to estimate the clinical acceptability and its accuracy. Further, the performance of different wearable in the heart rate estimation is listed and summarized in the Table 1.

TABLE I. Performance of proposed and HR estimation techniques for wearable's using PPG signals

Method	Max. Error (%) in BPM
Majid Farhadi, et. al. [12]	1.19
HSUM median [3]	1.57
SpaMA (Salehizadeh et al. 2015) [25]	1.59
WFPV (Temko 2015) [26]	2.61
JOSS (Zhang 2015) [27]	3.81

TROIKA (Zhang et al. 2015) [28]	4
HSUM [3]	2.4
Proposed	**1.4**

Here, the maximum absolute error (in BPM) using recently developed algorithms like Majid Farhadi, et al. [12], HSUM median [3], HSUM [3], SpaMA (Salehizadeh et al. 2015) [26], WFPV (Temko 2015) [27], JOSS (Zhang 2015) [28], and TROIKA (Zhang et al. 2015) [28] is listed for comparison in the Table 1. These results show the 0.7 % – 2.5 % of beats (1 – 2 BPM) may miss maximally from the standard 72 BPM during the estimation, where the Shannon entropy based HR estimation achieved with 1.4% error in BPM. However, the commercial wearable performance studies with compare to gold standard method in term of BPM deviation or error as reported in the literature is 5 – 10 BPM. However, the wearable/watch measures the time between heartbeats, its analysis, and providing health insights.

IV. Conclusion

Heart rate monitoring is very essential activity to avoid the major consequences especially in the post COVID-19 era. In this work, Shannon entropy based PPG signal analyzed for the HR estimation that further extended for the IBI and HR variability for details clinical exercise. The results shows the suitability of proposed method with less error rate as compare to the existing methods and gold standards. However, research comparing the performance of commercial wearable's to gold standard methods show a BPM variance or error of 5 to 10 BPM. Despite this, wearable's continue to measure the time between heartbeats and provide significant health information through their analysis.

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