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A Survey of AI-based Approaches for Processing Photoplethysmography Signals

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Abstract

Photoplethysmography (PPG) is a non-invasive optical technique that measures physiological parameters like heart rate, blood oxygen saturation, and blood volume. However, PPG signals are often noisy and contaminated with artifacts, posing challenges to inaccurate measurements. To address this, artificial intelligence (AI) techniques have been employed by many researchers to improve PPG signal processing. This paper presents a comprehensive survey of AI-based approaches for processing PPG signals in recent years. Various AI techniques, including machine learning, deep learning, and natural language processing, are discussed in relation to their application in PPG signal analysis. The limitations and challenges associated with AI-based approaches in this context are also explored. Furthermore, future research directions are highlighted to leverage AI's potential for revolutionizing PPG signal processing and expanding its applications. By examining the latest advancements, this survey aims to guide researchers and practitioners in understanding and harnessing AI-based methods for enhanced PPG signal processing, contributing to improved healthcare monitoring and diagnosis.

Keywords: Blood flow, Photoplethysmography, Optical sensors, Noninvasive

1 Introduction

In recent years, there has been a surge of interest in the development of non-invasive, cost-effective, and user-friendly methods for monitoring blood flow [36] . One promis- ing technology in this regard is Photoplethysmography (PPG), which employs a light source and a detector to measure changes in blood volume within peripheral tissues [24] . PPG signals provide valuable cardiovascular information and find applications in diverse fields, including healthcare, sports, and wellness [2] . However, processing PPG signals poses challenges due to noise, motion artifacts, and inter-individual variabil- ity [33] . The objective of this manuscript is to comprehensively review state-of-the-art AI-based approaches for the processing of PPG signals [3] . Additionally, we will discuss the advantages, limitations, and potential applications of these approaches.

PPG signals offer a wealth of information beyond just oxygen saturation level (SpO2) [40] , making them suitable for affordable, rapid, and non-invasive healthcare applications [39] . Notably, PPG technology has become increasingly accessible, cost- effective, and seamlessly integral into portable devices [42]. The advent of smartphones and wearable devices capable of capturing pulse oximeter signals has further propelled advancements in this field [17]. Consequently, we anticipate that accurate and contin- uous blood pressure measurements may soon be attainable from mobile and wearable devices, harnessing their immense potential [19] .

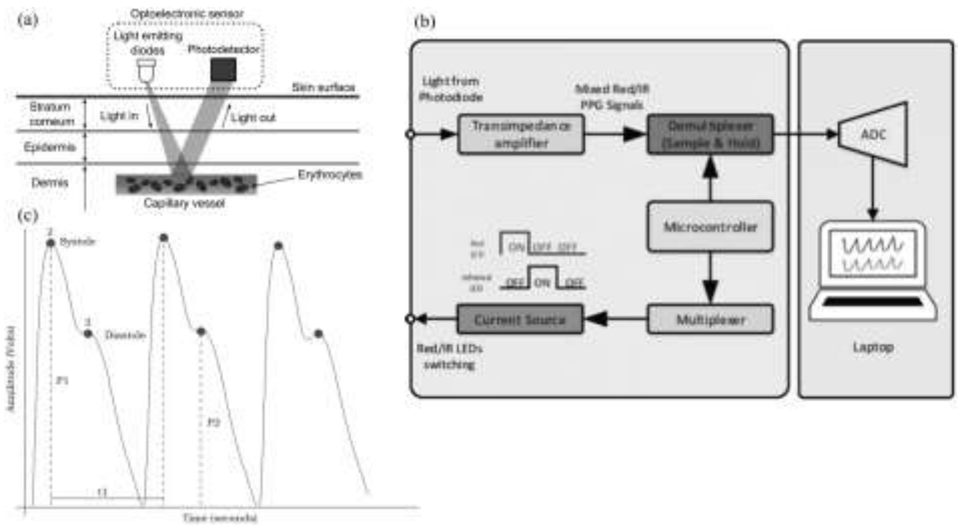

Fig. 1: (a) Concept diagram of opto-electronic PPG sensor. (b) Signal Processing of PPG signal (c) Aquired PPG signal

Figure 1a shows the conceptual diagram of an opto-electronic PPG sensor . The figure shows the basic components involved in the measurement process, including a light source and a detector [4] . The light source emits light into the tissue, and the detector measures the changes in light absorption caused by blood volume changes [1] . This diagram demonstrates the non-invasive nature of PPG sensing and highlights the principle of using light to assess physiological parameters [31] [8] . Figure 1b shows the signal processing involved in analyzing PPG signals. It illustrates the various stages of signal processing, including Trans impedance amplifier followed by sample and hold circuit [38] with integrated demultiplexer and multiplexer followed by current source to produce pulses at trasmitter end of Opto-electronic device [41] . The high resolution ADC is crucial to enhance the quality of the PPG signal [25] and enable accurate measurement of physiological parameters on to a laptop. Figure 1c shows acquired PPG signal [6] . This figure displays an systole and distole values of PPG. It represents the waveform obtained from the PPG sensor, showing the fluctuations in blood volume over time. The PPG signal typically consists of distinct peaks and valleys that correspond to different physiological events [44] [13] , providing valuable information about the cardiovascular system.

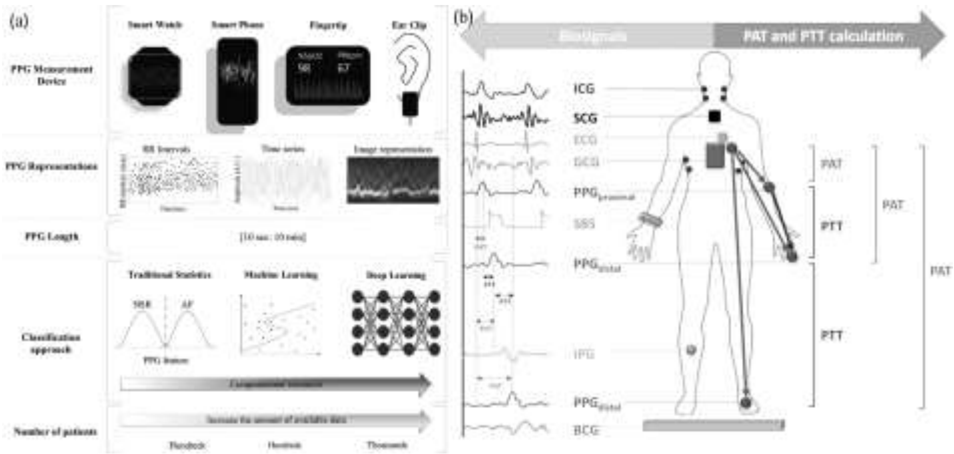

Fig. 2: (a) Generalized concept diagram of the processing of PPG signals. PPG measuring devices could be a smartwatch or smartphone, a fingertip device or it could even your ear clip. PPG representation is generally done in terms of RR intervals [37] or time

series or even used as a 3d image generated from PPG signal data. PPG length can vary between 10 sec to 10 minutes [15] . The classification approach could be Tra- ditional mathematics based or it could be ML based or even it can be DL based [11]
. The computational resources increase with each approach as well as data required for each approach also increases. (b)Different body signals and how the combination of these signals is used in PAT and PTT [10] . PPG signals can be collected from multiple places and can have multiple types.

Figure 2a illustrates a generalized concept diagram depicting the processing of pho- toplethysmogram (PPG) signals. PPG measurements can be obtained using various devices such as smartwatches, smartphones, fingertip devices, or ear clips [46] . PPG

data can be represented in terms of RR intervals, time series, or even transformed into a 3D image [12] [22] . The length of PPG recordings can range from 10 seconds to 10 minutes [7] . Classification approaches for PPG analysis can be based on traditional mathematics, machine learning (ML), or deep learning (DL) [27] , with increasing computational resources and data requirements for each approach [32] . In Figure 2b, different body signals are shown, highlighting how the combination of these signals is utilized in pulse arrival time (PAT) and pulse transit time (PTT) calculations [30] [9]
. PPG signals can be collected from multiple locations on the body and may exhibit various signal characteristics [21] .

2 PPG signal-based measurements

Azar et al. [5] addressed the need for fast and convenient cardiovascular analysis techniques using photoplethysmogram (PPG). They proposed a neural network-based filtering method to remove distorted signals caused by motion in PPG data, and a strategy for summarizing and augmenting the data to optimize network performance. Experimental results demonstrated a high precision of 90% and recall of 95% when processing PPG data collected from a Shimmer3 GSR+ sensor.

2.1 Blood pressure measurement

Figure 3a illustrates a diagram comparing the use of invasive arterial blood pressure (ABP) measurement with noninvasive photoplethysmography (PPG) for diagnostic purposes. Figure 3b depicts a schematic of a volume clamping device, where counter pressure is generated by an air pump and valve. A control system is employed to determine the appropriate counter pressure value. Figure 3c demonstrates oscilliome- try through a PPG force sensor unit, which measures PPG using a force sensor instead of the traditional optical method. Figure 3d displays a Normalized PPG Graph high- lighting key points of interest, including the maximum slope, systolic peak, dicrotic notch, inflection point, and diastolic peak. Figure 3e demonstrates how Pulse Transit Time (PTT) is detected using PPG. Lastly, Figure 3f portrays a schematic for the feature extraction of PPG waveforms using feature extraction techniques.

Kilickaya et al. [18] proposed a cuffless and continuous monitoring method for estimating blood pressure using Photoplethysmography (PPG) signals. Traditional blood pressure measurement devices using sphygmomanometers are uncomfortable for patients, making this method an attractive alternative. The researchers used PPG sig- nals to extract useful information such as pulse arrival time (PAT) and pulse transit time (PTT) to estimate systolic and diastolic blood pressure values. To achieve this, three different machine learning algorithms, Linear Regression (LR), Support Vector Regression (SVR), and Artificial Neural Networks (ANNs), were implemented using PPG signals and other features such as body mass index (BMI), age, height, and weight obtained from the patient.
A new, short-recorded photoplethysmogram dataset was used to train and test the machine learning algorithms. The results were compared in terms of mean absolute error, and the performance of each algorithm was evaluated. The study demon- strated the feasibility of using PPG signals for continuous blood pressure monitoring,

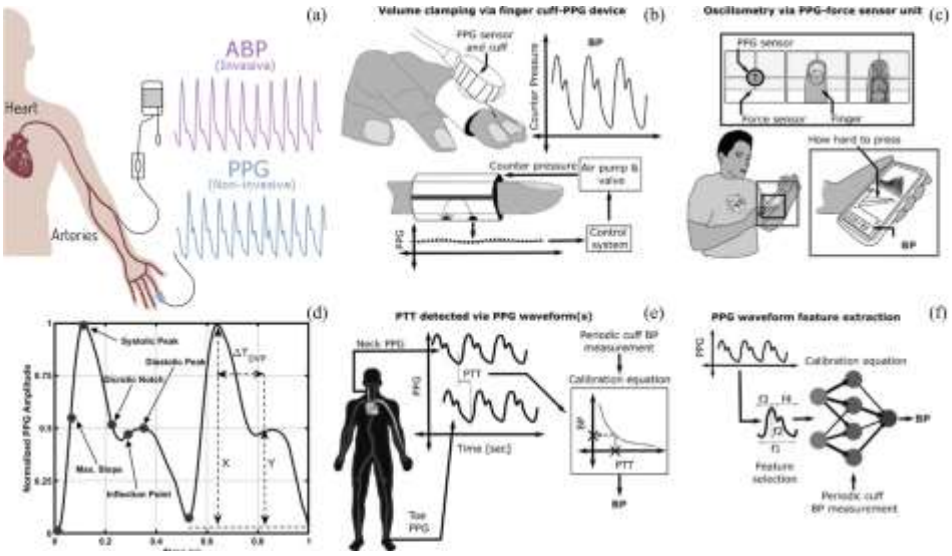

Fig. 3: (a) Schematic showing how arterial blood pressure (ABP) which is an invasive method versus photoplethysmography (PPG) which is a noninvasive method used in diagnosis. (b) Schematic of volume clamping device via figure cutoff (c) Oscilliometry via PPG force sensor unit (d) Normalized PPG Graph showing all important points to be considered. (e) Pulse transit time (PTT) detected using PPG (f) PPG waveform feature extraction schematic using feature extraction.

eliminating the need for a cuff. Additionally, the study highlighted the potential of machine learning algorithms in estimating blood pressure values using PPG signals and other patient-related features, thereby paving the way for non-invasive, low-cost, and convenient blood pressure monitoring.

Panwar et al. [23] developed a deep learning model called PP-Net that can simultaneously estimate diastolic blood pressure (DBP), systolic blood pressure (SBP), and heart rate (HR) from a single-channel PPG signal. The model utilizes the Long-term Recurrent Convolutional Network (LRCN) framework, which eliminates the need for costly feature selection and extraction. The model was evaluated on a large MIMIC- II database, achieving an average NMAE of 0.09 (DBP), 0.04 (SBP), and 0.046 bpm (HR) for a population of 1557 critically ill subjects, demonstrating its effectiveness in cardiac and stroke rehabilitation monitoring.

Hsu et al. [14] developed a deep neural network model that extracts 32 fea- tures exclusively from photoplethysmogram (PPG) signals to estimate blood pressure (BP). They aimed to create a generalized BP estimation model using PPG signals alone, reducing the need for additional sensors. The proposed model achieved high accuracy, with root mean square errors (RMSEs) of 4.643 mmHg for systolic blood pressure (SBP) and 3.307 mmHg for diastolic blood pressure (DBP), demonstrating its effectiveness compared to previous works.

Wang et al. [43] developed a transfer learning-based algorithm for estimating blood pressure (BP) using a few seconds of the photoplethysmography (PPG) signal. Their algorithm utilized visibility graph to create feature-rich images capturing waveform morphology. Evaluation on the MIMIC II database showed that the estimated systolic and diastolic BP had a difference of -0.080 10.097 mmHg and 0.057 4±814 mmHg, respectively,±indicating the effectiveness of their approach for BP estimation.

Qin et al. [26] conducted a review of recent research on cuffless continuous blood pressure monitoring using photoplethysmography (PPG) signals. They searched for relevant studies in databases like Web of Science and PubMed and identified common trends in the field. The paper covers the use of open datasets, signal preprocessing techniques, and evaluation criteria. It highlights the progression from early studies using linear equations and pulse wave velocity to more advanced approaches involving machine learning and deep learning models for blood pressure prediction. The authors conclude by discussing the challenges and opportunities for the development of cuffless continuous blood pressure monitoring technologies.

2.2 Werable device

Fig. 4: PPG acquiring device mounted on (a) finger, (b) wrist band (c) smartwatch (d) ring. (e) Schematic showing different positions on the body at which PPG measure- ment can be conducted. (f) Polar OH sensor mounted on glasses as well as mounted side by side with various smartwatches.

Figure 4 illustrates the PPG acquiring device positioned on various body parts and wearable devices. In figure 4a, the PPG device is mounted on the finger, while in figure 4b, it is mounted on a wrist band. Figure 4c demonstrates the device being integrated into a smartwatch, and in figure 4d, it is shown mounted on a ring. Figure 4e provides a schematic displaying different positions on the body where PPG measurements can be performed. This highlights the versatility and flexibility of PPG technology for acquiring physiological data from various locations. figure 4f showcases a Polar OH sensor mounted on glasses, as well as positioned side by side with different smartwatches. This demonstrates the potential integration of PPG technology into wearable devices, enabling continuous monitoring of vital signs and health parameters. Labra et al. [34] developed a multi-channel Photoplethysmography (PPG) wearable system for tracking human vitals, which can be used for applications such as exercise, wellness, and health monitoring. The PPG sensor measures pulse rate, cardiac cycle, oxygen saturation, and blood flow by passing a light beam of variable wavelength through the skin and measuring its reflection. The wearable system as ahown if Fig. 2a includes multiple nodes of pulse oximeters, each capable of using different wavelengths of light. The system uses sensor fusion along with a machine learning model to perform feature extraction of relevant cardiovascular metrics across multiple pulse oximeters and predict saturated oxygen (SpO2). The developed model predicted SpO2 with high accuracy, as demonstrated by the root mean square (RMSE) of 0.07 and accuracy of 99.5%. The wearable system was applied to the foot for vascular assessment, indicating its potential application in the continuous evaluation/monitoring of wounds and diseases associated with abnormal blood flow.

Zhang et al. [45] have conducted a comprehensive analysis of deep learning methods used for human activity recognition (HAR) on mobile and wearable devices. They categorized and summarized existing work in this area, highlighting the advancements, trends, and challenges. The paper also presents cutting-edge frontiers and future directions for deep learning-based HAR, emphasizing its potential for improving activity tracking, wellness monitoring, and human-computer interaction.

2.3 Deep neural network

Lampier et al. [20] developed a U-net shaped Deep Neural Network (DNN) model to extract remote photoplethysmography (rPPG) signals from skin color signals and estimate Pulse Rate (PR). They used three window sizes (256, 512, and 1024 samples) as input to the DNN and employed a data augmentation algorithm for training. The proposed model outperformed a prior-knowledge rPPG method, achieving lower Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) values, indicating its potential for reliable and faster PR estimation even with short window lengths.

Jothi et al. [16] developed a deep learning framework to automatically detect obstructive sleep apnea (OSA) events from Photoplethysmogram (PPG) signals recorded at the finger tip. They compared three deep learning approaches (Bi-LSTM, TCN, and TCN-LSTM) using datasets from Physionet's apnea database and real-time PPG signals of 315 subjects with various health conditions. The TCN-LSTM approach demonstrated the best performance, achieving an accuracy of 93.39%, specificity of 94.37%, sensitivity of 98.98%, and F1 Score of 94.12%, enabling real-time and efficient OSA screening.

Radha et al. [29] developed a deep recurrent neural network to classify sleep stages using photoplethysmography (PPG) data from wrist-worn wearables. They faced the challenge of limited PPG data in large sleep studies, so they trained the network using a larger dataset with electrocardiogram (ECG) data and then fine-tuned it with a smaller PPG dataset using transfer learning. Their approach achieved unprecedented performance (Cohen's kappa of 0.65 and accuracy of 76.36%) for PPG-based sleep stage classification, indicating its potential for clinical use. Further research is needed to evaluate its effectiveness in patients with sleep disorders.

Qiu et al. [28] provide an overview of remote heart rate estimation from video images as a potential cost-effective and comfortable method for medical and health care applications. They explain the principle of remote photoplethysmography sig- nal extraction and discuss mathematical models, computational algorithms, and deep learning methods for addressing movement artifacts and illumination changes. Addi- tionally, they review available datasets for remote photoplethysmography learning.

Roh et al. [35] developed a machine learning model that accurately evaluates the quality of a photoplethysmogram (PPG) using the shape and phase relevance of the waveform. They recorded PPGs from 76 participants, segmented them into pulsatile segments, and manually labeled them as 'good' or 'poor'. Their convolutional neu- ral network model achieved a balanced accuracy of 0.975, correctly classifying 48,827 out of 49,561 segments, with a sensitivity of 0.964 and specificity of 0.987. This model, using recurrence plots as input, can assess signal quality without complex preprocessing or feature detection processes.

3 Discussions:

3.1 Exploring the Potential of PPG Technology

The subsection highlights the importance of gaining a deeper understanding of photo- plethysmography (PPG) and its connection to various pathophysiological phenomena. Researchers are revisiting basic PPG research to develop the necessary tools and pro- cesses for enhanced comprehension. This includes a focus on understanding light-tissue interactions across multiple wavelengths and sensor topologies.

Furthermore, the exploration of PPG in biometrics is discussed, with a focus on leveraging artificial intelligence (AI) signal processing techniques to improve PPG biometric applications. The subsection covers fundamental topics, such as PPG theory, technology, and signal analysis, as well as its diverse clinical and consumer applications.

Table 1: Comparison of different AI-based PPG signal processing techniques

	Accuracy
Eenia et al.	98%
Pei et al.	88.61%
Ignacio et al.	99.5%

norani et al.	80%
Ji woon et al.	81%

In Table 1, a comparison is presented, showcasing various AI-based PPG signal processing techniques in terms of their accuracy. The study conducted by Ignacio et al. demonstrated the highest level of accuracy, reaching an impressive 99.5%. Their research involved the creation of a wearable device capable of monitoring the cardio-vascular matrix. On the other hand, Norani et al. reported the lowest accuracy of 80% in their study. They focused on measuring Neonatal Heart disease by analyzing dynamic scattering in the PPG signal.

4 Conclusions

In conclusion, this paper offers a comprehensive overview of recent advancements and applications of artificial intelligence (AI) techniques in the processing of Photo-plethysmography (PPG) signals. PPG, a non-invasive optical technique, is utilized for measuring physiological parameters such as heart rate, blood oxygen saturation, and blood volume. However, PPG signals are often prone to noise and artifacts, resulting in inaccurate measurements. To address these challenges and enhance PPG signal processing, various AI techniques including machine learning, deep learning, and natural language processing have been explored.

The paper thoroughly examines the advantages, limitations, and potential applications of AI techniques in PPG signal analysis. The utilization of AI methods holds the potential to revolutionize PPG signal processing and expand its applications in healthcare monitoring and diagnosis.

Moreover, the paper highlights notable studies that apply AI for specific purposes in PPG signal processing. For instance, Azar et al. propose a neural network-based filtering method to eliminate motion artifacts from PPG data, while Kilickaya et al. develop a cuffless and continuous blood pressure monitoring approach using machine learning algorithms and PPG signals. Other studies focus on estimating blood pres- sure, heart rate, and detecting sleep disorders using deep learning models trained on PPG data.

In summary, this survey provides valuable insights into the current status of AI- based approaches for processing PPG signals. It underscores the potential of AI techniques in enhancing the accuracy and efficiency of PPG signal analysis, thereby contributing to improved healthcare monitoring and diagnosis. Additionally, the paper identifies future research directions, along with the challenges and opportunities in this field. Researchers and practitioners can benefit from this survey to gain a better understanding of and leverage AI-based methods for PPG signal processing.

Appendix A Data and code availability:

Data and code will be made available on reasonable request to the Authors.

Appendix B Supplementary information:

Not applicable.

Appendix C Ethical approval:

All the ethics approval was taken by an institutional review board or equivalent ethics committee.

Appendix D Funding statement:

This research has no funding associated with it.

Appendix E Competing interests:

Authors declare that there is no competing interests.

Appendix F Availability of data and materials:

Data and code will be made available on reasonable request to corresponding author.

Appendix G Ethics statements:

All authors consciously assure that the manuscript fulfills the following statements:

1) This material is the author's original work, which has not been previously published elsewhere.
2) The paper is not currently being considered for publication elsewhere.
3) The paper reflects the author's own research and analysis truthfully and completely.
4) The paper properly credits the meaningful contributions of co-authors and co-researchers.
5) The results are appropriately placed in the context of prior and existing research.

Appendix H Conflicts of interest or competing interests:

Authors declare that there is no Conflict of interest or competing interests.

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