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Photoplethysmography in Cardiovascular Disfunction Detection: Signal Processing, Analysis, Implementation. A Review

B.T. Śmigielski, M.N. Chołuj and G. Cybulski*

Faculty of Mechatronics, Institute of Metrology and Biomedical Engineering, Warsaw University of Technology, św. A. Boboli 8, 02-525 Warsaw, Poland

Doi: 10.12693/APhysPolA.146.600 *e-mail: gerard.cybulski@pw.edu.pl

Photoplethysmography is a non-invasive physical method used for monitoring arterial blood flow in the subject's body by measuring the amount of light absorbed or reflected by the pulsatile blood flow within the vessels. It is commonly used in wearable devices, primarily for pulse measurement. In ambulatory and clinical practice, it is implemented in pulse oximetry for the estimation of pulse and blood oxygen saturation levels. However, this method has the potential for a much broader range of measurements, such as detecting atrial fibrillation episodes. Innovative applications of this field continue to emerge in the analysis of the cardiovascular system, along with the implementation of new technological solutions aimed at analyzing and improving signal quality. Thus, we have decided to collect information on the current advancements in the field of photoplethysmography. Also, the aim of this mini-review was to bring closer non-obvious applications of photoplethysmography and its development prospects.

topics: photoplethysmography, cardiovascular, signal analysis, signal processing

1. Introduction

Photoplethysmography (PPG) is a non-invasive physical method used for the measurement and monitoring of arterial blood flow in the subject's body with the application of light. PPG is based on the measurement of light absorbed or reflected by the pulsatile blood flow within the vessels. It is used to assess a range of parameters related to the human cardiovascular system. It is based on measuring the intensity of light emitted from a device's light source (traditionally *light-emitting diode* (LED)) after passing through the patient's tissue towards the receiver. PPG devices may be applied in various places on the patient's body, like a finger (typically), wrist, or earlobe. This method is easy to implement and is increasingly being used not only in clinical practice, but also in larger market devices, such as phones (commonly with the use of a flashlight as the main light source) and smartwatches.

Earlier, red light (wavelength around 645 nm) was commonly used, but new studies show that the application of green light (around 530 nm) improves signal-to-noise ratio values [1]. The difference in obtained amplitudes originates in the intensity of the light source and the molar absorption coefficient of the wavelength, a parameter describing the absorption of light by blood for a certain wavelength. This coefficient was parameterized by Scott Prahl [2] based on studies reported in [3, 4]. PPG technology in clinical or wearable devices requires basic optoelectronic components with a stable *continuous-wave* (CW) light source to illuminate the tissue and a photodetector to measure the small changes in the reflected/absorbed light intensity associated with variations in blood perfusion. In the commercially available systems, neither photon distribution time of flight nor phase shift are analyzed, which might be important, especially in obese people [5].

The PPG trace has a distinctive shape, as presented in Fig. 1. The characteristic points marked in Fig. 1 are described in the literature and are commonly used for PPG data analysis [6].

Photoplethysmography is a rapidly developing field of research, due to the relatively simple implementation of the PPG method and the wide range of data that can be obtained from the PPG signal. The aim of this work was to review articles not older

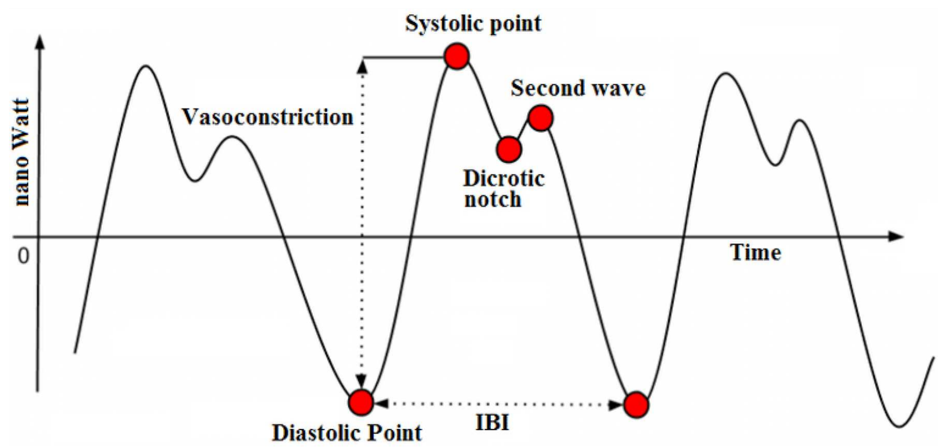

Fig. 1. Example of PPG signal with marked characteristic points, adapted from [6].

than five years to present the main problems in the development prospects of PPG and to bring closer typical as well as non-obvious applications of that method.

2. Methods

2.1. The research

The articles reviewed in this paper were primarily searched in the Institute of Electrical and Electronics Engineers (IEEE Xplore) database using keywords such as photoplethysmography, PPG, atrial fibrillation, algorithm, blood pressure, and heart.

2.2. Paper selection criteria

The selected articles were published between 2019 and 2024, covering a maximum of the past five years. The studies described in these articles include innovative solutions for disease detection and the examination of physiological parameters, as well as new techniques for PPG signal recording and quality improvement.

2.3. Organization

The collected studies have been divided into four sections describing the improvement of the PPG in:

- Methods of signal recording,
- Signal quality,
- Possibility of disease detection,
- Examination of physiological parameters.

Some sections also contain thematic subsections to underline the uniqueness of the problem.

3. Analyzed materials

3.1. Methods of signal recording

Photoplethysmography methods are based on light, the source of which is often the most energy-consuming part of the measuring device. This problem was considered in article [7], where the authors introduced and tested the NO-LED device based on the external light source.

The study was conducted with two volunteers, each undergoing five-minute measurements under the following conditions:

- Indoors:
  - Ceiling lighting,
  - Sunlight six meters from the window,
- In direct sunlight,
- In diffuse sunlight.

For each situation, the authors provided the average light intensity falling on the measurement system. The results were compared with a reference device. The authors consider the results obtained by the proposed system as “reliable or acceptable” and highlight the difference in power consumption between the device using LED and the NO-LED mode.

Nowadays, it is also common to collect PPG data using smartphones. Mostly, these devices have at least one front and one back camera, which can be used for data gathering. In article [8], the quality of photoplethysmographic readings obtained using the front and rear cameras of a smartphone were compared.

The study involved the simultaneous collection and comparison of measurements from three sources:

- Front camera (finger illuminated by the phone screen),
- Rear camera,
- Reference device.

As a result of the experiment, the authors concluded that using the front camera of the phone allows for greater control over the emitted light, which in turn can improve the quality of the obtained signal. Additionally, new possibilities were identified, such as using the screen to detect the presence and movements of the subject's finger, which could be used, for example, to assess the quality of the measurement.

3.2. Signal quality improvement

The common problem with PPG signals is the elimination of motion artifacts and noise generated by other sources. In article [9], the authors described a method for removing motion artifacts in PPG signals based on a one-dimensional convolutional neural network and single-cycle wave analysis. The dataset used in the experiment consisted of 240 correct and 220 incorrect cycles of *normal sinus rhythm* (NSR) and *atrial fibrillation* (AF). The training-to-testing data ratio was 4:1.

The quality control model achieved results of *area under the curve* (AUC) and accuracy = 98%, sensitivity = 99%, and specificity and precision = 97%. By removing the disturbed cycles detected by the model, the authors claimed to by able to improve the detection of atrial fibrillation in PPG signals from 85.5% to 95.5%.

3.3. Possibility of disease detection

3.3.1. Coronary heart disease (CHD)

PPG signals have a wide range of applications in disease detection. Most of them are associated with heart disfunction. In article [10], the authors focused on detecting *coronary heart disease* (CHD) with a PPG signal. The paper presents a review of the literature on CHD detection using PPG, as well as a discussion and comparison of the effectiveness of three types of algorithms: RR interval-based, *heart rate variability* (HRV) feature-based, and time-domain feature-based.

The algorithms were tested using data collected from a group of 58 individuals — 28 with CHD and 30 healthy controls. As a result of the experiment, it was determined that the HRV feature-based algorithm demonstrated the best performance, with an accuracy of 94%, sensitivity of 100%, and specificity of 91%.

3.3.2. Diabetes prediction

Not only heart disfunctions can be detected using PPG signal. In article [11], the authors described a convolutional neural network they developed and tested for detecting diabetes based on scalograms generated from PPG signals. The model was trained and tested using data collected from 808 patients (224 in test group). The achieved accuracy was 76%, and the AUC was 83%. The authors also suggest that deep learning techniques may be more effective than traditional machine learning due to the presence of motion artifacts.

3.3.3. Atrial fibrillation (AF)

The most common type of arrhythmia is *atrial fibrillation* (AF). We focused on three original studies describing AF detection.

In article [12], the authors presented a program for detecting atrial fibrillation (AF) in PPG signals using variational mode decomposition with variables. The program was tested using the publicly available MIMIC PERform AF database [13], which contains data collected from 35 individuals (19 with AF and 16 healthy). The achieved accuracy, sensitivity, and specificity were approximately 99%. The authors also demonstrated that the developed system enables real-time analysis.

The authors of the second study [14] proposed different a approach describing the detection of AF using short segments of PPG signals ($\approx$ 15 s). The method was based on extracting musical features from the signal. The authors developed two computer algorithms: the first, written using the classical approach, achieved an accuracy of 89%, while the second one, based on machine learning, achieved an accuracy of 95%. The effectiveness was validated using the MIMIC PERform [13] dataset. The advantages of this approach include the short length of the signal segments analyzed.

In the third article [15], the authors again proposed detecting atrial fibrillation (AF) using short segments of PPG signals ($\approx$ 15 s). This time, the program was based on a deep convolutional neural network. The program was tested using the MIMIC database. Three different network models were applied, with the highest accuracy reaching 99%.

3.4. Hypertension

The possibility of detecting hypertension with PPG signals was analyzed in another study [16]. The authors presented a convolutional neural network that categorizes the level of hypertension based on predicted blood pressure and a range of patient parameters derived from the PPG signal. The algorithm was trained and tested using a dataset of 657 PPG recordings from a group of 219 patients. The achieved accuracy, sensitivity, and specificity of the results were at approximately 95%.

3.5. Examination of physiological parameters

3.5.1. General health condition

The popularity of commercially available PPG-based wearable devices demonstrates a demand for continuous monitoring of physiological parameters, which stimulates research on extracting additional information regarding general health and well-being from PPG. The authors of [17] compared two techniques for extracting information from the PPG signal, namely fiducial point analysis and symmetric projection attractor reconstruction. The aim of the paper was to identify a set of data that would allow the classification of PPG signals based on gender, age, and physical activity. The study was conducted using three data sets:

- An artificial data set simulating PPG signals of healthy males aged 25–75 years,
- A set of ten-minute measurements taken from 57 healthy individuals at rest,
- A set of measurements collected over four weeks from the same study participants.

The results of the study demonstrated that both techniques are useful in identifying cardiovascular differences between patients as well as within a single patient. These techniques can be used for classification based on age and physical activity, but not by gender.

3.6. Blood pressure

PPG measurements enable a simplified way of indirect estimation of *blood pressure* (BP). No need for using a cuff and the possibility of building PPG systems into wearables such as smartwatches enable everyday blood pressure monitoring, which can be helpful for many people, including those at risk of hypertension. We gathered four original papers about BP estimation.

In the first article [18], the authors addressed the issue of overestimating the accuracy of models used for monitoring arterial blood pressure. The discussion focuses on machine learning models that were trained and tested on the same dataset. The authors compared the results of cross-validation (using data from the same dataset) with external validation, where the model is tested on a new dataset in a regression model based on PPG features. The study utilized data from the PhysioNet database [19], specifically the "Continuous Cuffless Monitoring of Arterial Blood Pressure via Graphene Bioimpedance Tattoos" dataset. This dataset contains measurements from 7 patients, both at rest and during specific test activities designed to induce blood pressure changes. The authors pointed out that while the results show a small mean absolute error in cross-validation, they also demonstrate "poor generalization ability in an external-validation scenario."

The second article [20] describes an algorithm for calculating blood pressure using PPG signals obtained with the Senbiosys ring, a device capable of continuous "ultra-low power" PPG monitoring.

The study was conducted with six male participants. Measurements were taken using both the Senbiosys ring and a cuff-based sphygmomanometer as a reference. In total, seventeen recordings were collected, each lasting between one and a half to two and a half hours.

Deviations from the reference device were:

- 0.28 ± 7.54 mmHg for systolic pressure,
- 1.30 ± 7.18 mmHg for diastolic pressure.

The authors also pointed out that these results meet the requirements of the ISO/ANSI/AAMI protocol, which specifies a deviation of 5 ± 8 mmHg.

The third article [21] describes an algorithm for estimating BP values using a camera. The analysis focused on video recordings of the subjects' foreheads, from which a feature vector was extracted and then processed using the Random Forest generator algorithm.

The algorithm's performance was tested using data collected from a group of 40 male volunteers aged 17 to 42. The subjects were healthy, and their skin tones varied. The results were compared to a reference device.

The obtained mean absolute errors compared to the reference sphygmomanometer were:

- 0.20 ± 6.41 mmHg for systolic pressure,
- 0.45 ± 12.39 mmHg for diastolic pressure.

In the future, the authors plan to increase the number of test data and the camera's operating frequency.

The fourth article [22] describes an algorithm for measuring blood pressure based on machine learning and the segmentation of signals into Poincaré sections.

The algorithm was tested using the Multiparameter Intelligent Monitoring in Intensive Care (MIMIC) II database, which includes arterial blood pressure and PPG signals.

The algorithm achieved the following mean absolute errors:

- 2.1 mmHg for systolic pressure,
- 1.4 mmHg for diastolic pressure.

3.7. Response to an orthostatic test

The studies show that changes in the patient's position during PPG measurements affect the shape of the PPG curve. This phenomenon was examined and described in article [23].

As a part of the test, a group of 7 individuals (6 men and 1 woman) underwent a series of measurements during an active orthostatic test. Standard PPG shape indicators commonly found in the literature were used, and two new indicators were proposed: the time of occurrence of the maximum derivative on the ascending phase and the time of occurrence of the minimum derivative on the descending phase of the plethysmographic curve. The authors found a statistically significant difference in measurement results between the standing and supine positions ($p<0.05$). They also suggest that the proposed indicators could be used for non-invasive assessment of the cardiovascular system.

In another study [24], the authors highlighted the impact of orthostatic hypotension on the increased risk of developing atrial fibrillation. The aim of the study was to illustrate the effect of orthostasis on the autonomic nervous system and to identify the characteristics of the pulse wave in patients with chronic atrial fibrillation during orthostasis.

The study was conducted with a group of two individuals undergoing an orthostatic test. Measurements were made using PPG and *electrocardiography* (ECG) signals.

The authors noted differences between the characteristic features observable in ECG and PPG measurements. In the case of ECG, the pulse wave shows increased irregularity in the intervals between QRS complexes. In the case of PPG, a dual change can be observed — an increase in irregularity in both the frequency and amplitude of the signal.

4. Conclusions

This article describes 16 studies covering various scientific achievements in the field of photoplethysmography. The materials address topics such as the examination of vascular system parameters and the detection of its diseases, as well as methods for acquiring, analyzing, and improving the quality of PPG signals. Diverse methods employed were described, utilizing modern techniques and devices, such as machine learning and wearable devices for long-term patient monitoring. We are convinced that advanced analysis of photoplethysmographic signals might bring additional information useful for general healthcare, which seems to be an inspiration to develop both signal generation and analysis methods.

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