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Review Article

PPG Signal and application in the medical field

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ABSTRACT

The ascent of remote health examination is a burgeoning trend in healthcare, aimed at tackling the challenge of hospital overload and streamlining the process of patient monitoring. To achieve these laudable goals, a device that is both efficient and capable of extracting critical health indicators is of paramount importance. Enter photoplethysmography (PPG) technology - a compact and user-friendly device that offers a wealth of health-related information. PPG is an optical, non-invasive method of measuring changes in blood volume in tissue by illuminating the skin and detecting variations in light absorption caused by blood flow. This technique has a multitude of applications, including the measurement of blood oxygen saturation, the estimation of blood pressure, the assessment of vascular aging, and the detection of arrhythmias. Therefore, it presents a promising avenue in addressing the challenge of hospital overload. This article provides an all-encompassing overview of photoplethysmography (PPG) technology, elucidating the underlying principles and highlighting its noteworthy applications. Specifically, the article expounds on the use of PPG in measuring blood oxygen saturation, estimating blood pressure, assessing vascular aging, and detecting arrhythmias. Despite the advantageous applications of PPG, there are still some issues that need to be addressed, such as the limited availability of PPG data sets in certain populations, the sensitivity of PPG signal to motion and ambient conditions, and a lack of clarity about the nature of PPG which leads to the absence of standard criteria in sampling and interpretation of PPG in its applications. And these issues are also thoroughly discussed in the paper.

Key words: photo-plethysmography, photo-plethysmography applications, photo-plethysmography principle

INTRODUCTION

The recent SARS - CoV - 2 pneumonia is an extremely dangerous disease due to its unpredictable and highly contagious nature. As a patient is infected with this disease, monitoring the *peripheral oxygen saturation (SPO2)* index regularly will help a lot in the monitoring of patient conditions. This is quite understandable because the SPO2 index indicates whether the amount of oxygen in the blood is sufficient to sustain life,[1], especially for COVID patients who have severely impaired lung functions. Besides, monitoring SPO2 levels at home using a pulse oximeter device can be very helpful before hospital admission for treatment,[2]. The technology that is used to measure SPO2 is named *photo-plethysmography (PPG)* technology. And not only measure SPO2, but this technology is also able to be used in health monitoring of its simplicity and effectiveness.

Since the first introduction in the mid-1930s, there have been over 5910 publications regarding the PPG signals and over 39281 citations,[3], regarding the extraction of information in the PPG signal to diagnose and detect cardiovascular diseases. Well-known research topics include calculation of blood pressure from PPG signals, the prediction of cardiac arrhythmias and the estimation of vascular aging,… Figure 1 shows the PPG research situation, Table 1 gives a summary of fields that has the application of this signal.

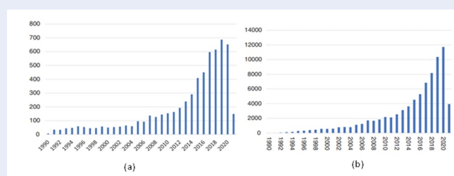

Figure 1: (a) The amount of publications regarding PPG, (b) The amount of citations in researches related to PPG[3].

With the enormous amount of critical information involved in health conditions, the devices used to record PPG signals have an incredibly simple design consisting of a light emitter *(LED - light-emitting diode)* and a light sensor *(photodiode)*, Figure 2. This is also a fascinating point of PPG signal compared to other biological signals, the technology can be easily integrated into small devices such as smartwatches and smart-

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Table 1: Fields that apply the usage of PPG signals[3].

Blood oxygen saturation	Venous assessment
Tissue viability/perfusion	Biometrics
Heart rate	Mental health
Heart arrhythmias	Endothelial function
Blood pressure	Microvascular blood flow
Cardiac output	Vasospastic conditions
Respiration	Autonomic function monitoring
Sleep studies	Vasomotor function and thermoregulation
Vascular assessment	Pulse Rate Variability (PRV)
Arterial disease	Other cardiovascular variability assessments
Arterial compliance and aging	Health and wellbeing

phones. There have even been *fitness trackers* that utilize PPG technology for athletic activities, for example, Oura (generation 3), Fitbit Charge 5, E4 wristband. As a result, remote health monitoring, diagnosis, or online hospitals becomes highly effective.

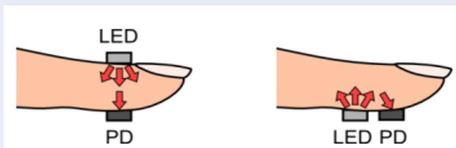

Figure 2: A PPG device consists of a light emitter (LED) and a light sensor (PD-photodiode)[3].

This paper provides a general overview of PPG technology and will be divided into three main parts. The first part will introduce the origin and principle of the PPG signal, explaining the device and factors that might affect the PPG signal. The second part will present a summary of research on the applications of PPG, including the calculation of SPO2, blood pressure, diagnosis of cardiac arrhythmias, and vascular aging. The final part will consist of discussions and a conclusion on the matter of the PPG signal.

THE NATURE AND PRINCIPLE OF PPG

Although there have been many studies surrounding PPG, such as Molitor and Kniazuk[4], Hanzlik[5], in 1936… However, the first to use the term *"photoelectric plethysmography"* was Hertzman and associates. Their first research on PPG was published in 1937, which showed that PPG shows changes in blood volume beneath the skin. Figure 3 shows PPG experiments from Hertzman's studies between 1937 and 1938, indicating an improvement in terms of compact design. Initially, Hertzman's PPG model lacked mobility, with both the emitter and the sensor attached to a fixed platform. In 1938, a more compact and mobile device was introduced that could be attached to the patient's hand. However, during this period, PPG devices were generally still inconvenient for public use. The 1960s saw the rapid development of semiconductor technology, and PPG became much more compact as a result, with the same principles suggested by Hertzman. Since then, more and more research on PPG has been conducted constantly. As a major development, PPG has been incorporated into measuring blood oxygen levels from 1990 to the present day.

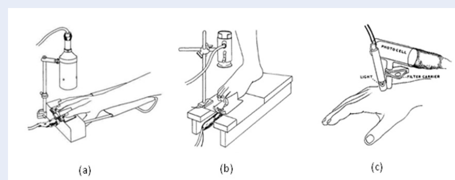

Figure 3: Hertzman's PPG devices throughout the years (a) (b) 1937, (c) 1938[3].

After a century of research, the most agreement definition was introduced: *"PPG signal is a voltage signal given by a light sensor (absorber) which records the reflected, scattered and partly absorbed light (through layers of tissues, blood) originated from a monochromatic light emitter."*[3], Figure 4.

From this definition, we can give two notices regarding the PPG signal. Firstly, different monochromatic lights will be absorbed differently by the body and give out different PPG signals as a result. This can be explained by the Beer-Lambert Law[3,6–8]. According to this law, the amount of light absorbed by a homogeneous medium can be determined as follow:

$$A = \varepsilon \times c \times l \tag{1}$$

Where A is the intensity of the absorbed light (absorbance), ε is the Molar absorption coefficient dependent on the medium, c is the molar concentration

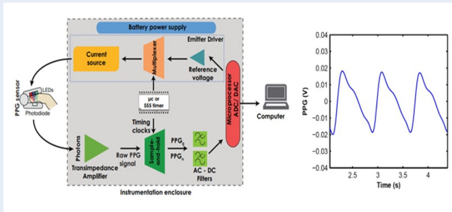

Figure 4: PPG signal acquisition system and PPG signal[3].

of the medium, l is the optical path in the medium. Taking the case of the PPG signal into consideration, the environment (medium) which the light travels through are tissues in the human body. This consists of many layers, Figure 5a, including cuticle, dermis, blood vessels, … As a result, based on different types of light sources, the PPG signals recorded at the same position will also be different. Figure 5b shows the absorption coefficient of each wavelength when traveling through different layers of tissues.

The types of monochromatic lights that are applied the most in PPG devices to measure oxygen level includes: blue light (500nm), red light (660nm) and infrared (940nm). Blue light has the shortest wavelength and, therefore, can be easily absorbed by the cuticle layer, resulting in its restricted ability to assess blood perfusion under the skin. Meanwhile, red and infrared light have longer wavelengths and are absorbed by hemoglobin, enabling them to reach larger and deeper vessels, including the arteries.

A special feature of the PPG signal is that it is in a waveform that oscillates according to the heart's cycle[3], particularly, the PPG signal from red and infrared light. This is because hemoglobin is transported throughout the body by red blood cells, and the amount of hemoglobin varies in sync with the heart's pump cycle. Hence, PPG can be used to calculate heart rate and other health indices such as SPO2. Furthermore, it can also be used to detect heart arrhythmia.

On the second matter, PPG signals will also differ depending on the configuration of the devices. Figure 6 shows the electrical models that can be used to collect the PPG signal. The first is the electrical model for the light source, which will typically only require a light source to create a PPG signal. However, in certain working conditions, the light source can be affected by many factors, making a filter system necessary to stabilize the electrical power source. Similarly, for the electrical model of the sensor, anti-noise measures are critical and require additional resistors and capacitors to create a low-pass filter. In some cases, two operational amplifiers can be used to increase efficiency. However, the addition of filters and different hardware configurations will greatly affect the form of the PPG signal. This is an important feature that requires attention during research and experiments.

From what has been discussed up to this point, we can produce a graph that generally presents the relations between our body parts and the PPG signal, as can be seen in Figure 7. A clear observation shows the information that the PPG signal can carry regarding the circulation system:

- The volume of blood flow can be determined through the intensity of the PPG signal.
- Heart rate is shown through the frequency of the PPG signal.
- Components of tissue and blood are shown through the absorption of different monochromatic lights at the position of sampling.
- The impacts of the arterial system on the position of sampling.

In brief, PPG signal is the response of a system created from the coordination of different organs which consists of the heart, blood vessels, control signals from the nervous system, and skin tissues at the position of sampling.

THE APPLICATIONS OF PPG

Measuring the saturation of peripheral oxygen (SPO2)

Oxygen enters the body through breathing and is transported by red blood cells throughout the body. This process is based on the oxidation of the *hemoglobin molecule (HHb)* in red blood cells resulting in *oxyhemologbin (O_2Hb)*. For each hemoglobin molecule, 4 oxygen molecules will be attached thus creating the O_2Hb; the peripheral oxygen saturation, SPO2, is the index indicating the ratio between O_2Hb molecules and HHb molecules[9]. SPO2 index is considered as an important vital sign alongside heart rate, blood pressure, and respiratory rate. As a normal standard, SPO2 is constantly monitored in emergency situations, Carbon monoxide poisoning diagnosis, and other conditions[10]. Nowadays, SPO2 is measured using PPG waves recorded from infrared and red lights[11]; this is based on the principle that O_2Hb and HHb absorption rate is different towards these two lights. Figure 8 shows the different levels of light absorption of O_2Hb and HHb for red light and infrared. For HHb, red light is absorbed more than infrared, and the opposite happens with O_2Hb.

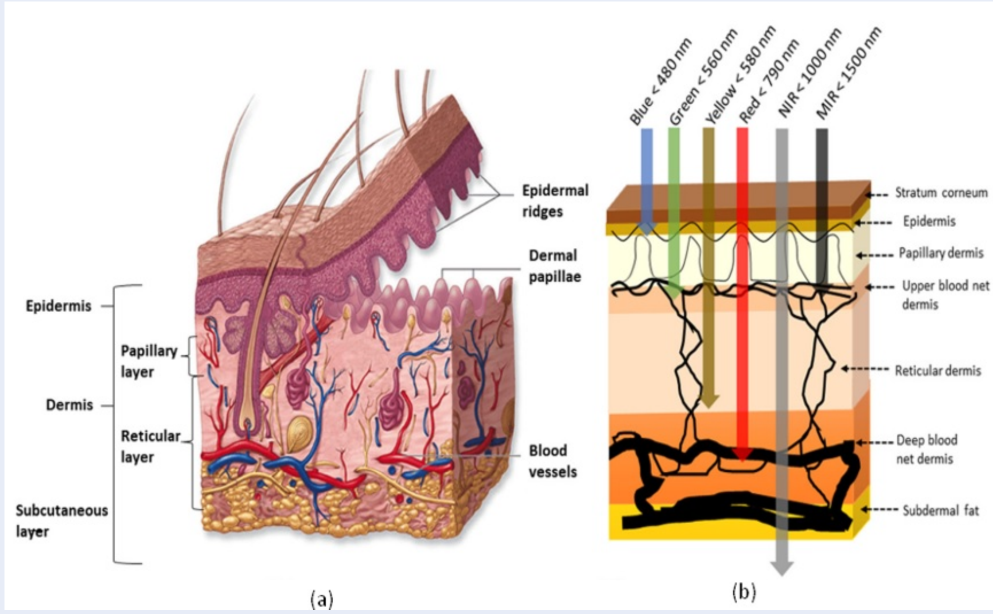

Figure 5: (a) Subcutaneous tissue structure, (b) different wavelengths of light have different penetration rates [3].

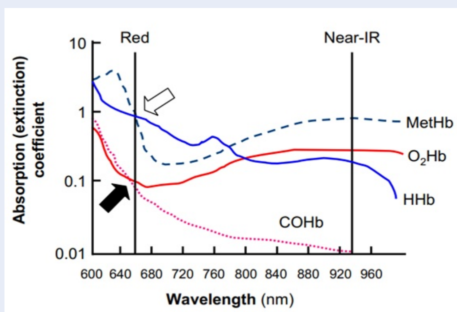

Figure 8: Different absorption rate of hemgolobin and oxyhemoglobin towards different wave-lengths of lights [6].

PPG signal from red and infrared light comes in a wave-form signal with its amplitude being in proportion with the concentration of oxygen in blood (when the concentration is at 70-100%), [6]. This is convenient as the PPG can give accurate measurements of oxygen concentration inside human's vital range. The formula for this is as follows [11]:

$$SpO2 = a - bR \quad (2)$$

Where

- $R = \frac{AC_R/DC_R}{AC_{IR}/DC_{IR}}$: coefficient of PPG amplitude ratio between infrared and red light.
- $AC_{R,IR}$: PPG wave-form amplitude, $DC_{R,IR}$: the bias component of the PPG signal, Figure 9.
- a and b are calibrating coefficients obtained through experiments ($107 \leq a \leq 110,25 \leq b \leq 32$)

Due to the compact design and simple principle, SPO2 measuring devices are widely used in home, clinical diagnosis in ambulance vehicles (by paramedics), and also in intensive care units. Furthermore, they can also be used during anesthesia sessions and to detect or monitor sleep apnea [12]. Figure 10 shows SPO2 measurement devices used in home, ambulances and in clinical situations.

Figure 10: SPO2 measuring devices are used from civil to clinical diagnosis. (a) Thiết bị đo SPO2, PO8, Beurer. (b) Đồng hồ thông minh Mi smart band 6, Xiaomi. (c) Thiết bị đo SPO2 AH-MX, Acare Technology Co., Ltd.

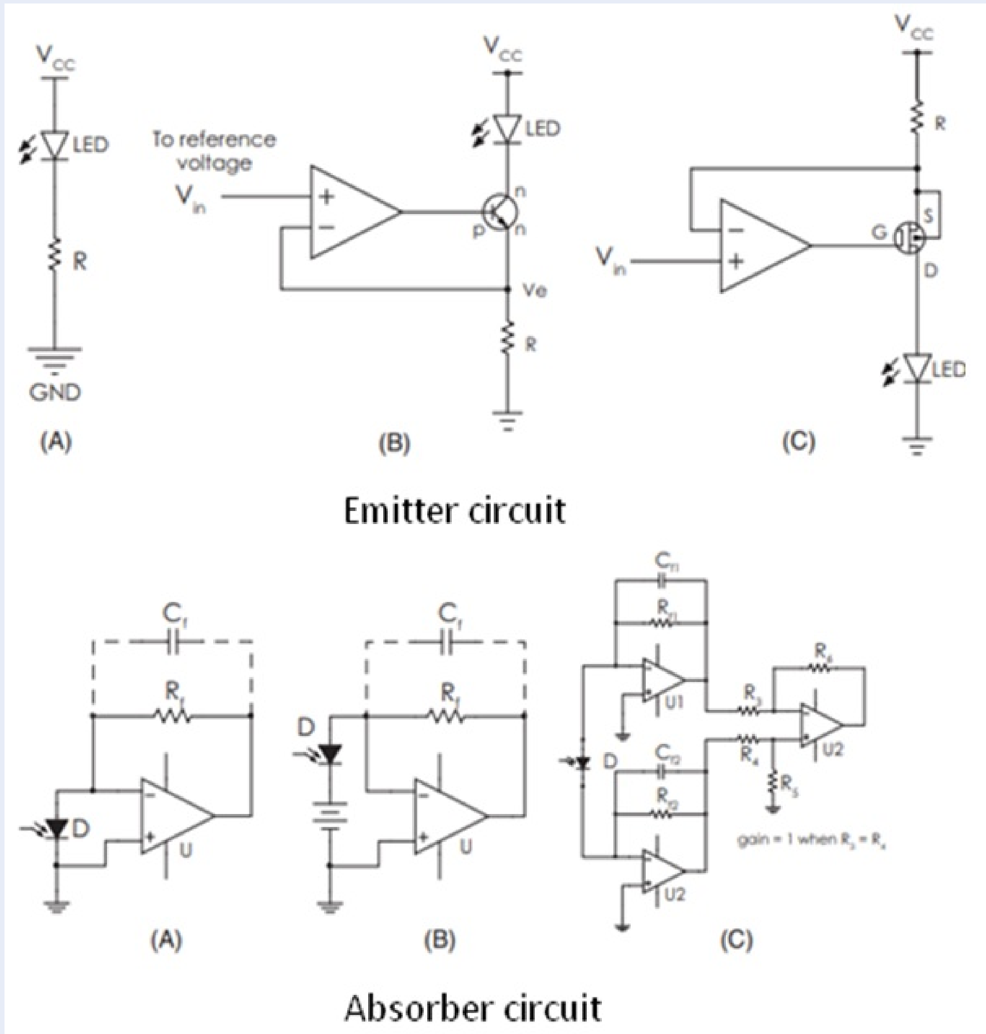

Figure 6: Circuit configuration for emitters and sensors in PPG devices [3].

Blood pressure

Blood pressure is the pressure applied on the vessel's wall by the pumping action of the heart, it can be described in a form of pressure wave, Figure 11. Based on this pressure wave, some definitions are established,[13].

- *Systolic pressure - SBP* is the highest value of the pressure wave.
- *Diastolic pressure - DBP* is the highest value of the pressure wave.
- *Mean arterial pressure – MAP* calculated using the following formula:

$$MAP = P_{dias} + \frac{1}{3}\left(P_{sys} - P_{dias}\right) \quad (3)$$

In which, MAP is the mean arterial pressure, P_{dias} is the diastolic pressure, P_{sys} is the systolic pressure. Monitoring of blood pressure is of critical importance, as a high blood pressure is the sign of serious illness such as kidney failure, stroke, heart failure, … Furthermore, the constant assessment of arterial blood pressure in its wave form provides many useful data for healthcare, especially in assessing vessel's aging and high blood pressure [14]. Currently, the blood pressure monitoring is conducted using a *sphygmomanometer*, Figure 12. A sphygmomanometer functions under the principle of creating air pressure to compare to arterial blood pressure [15]. Although being widely used in civilian and clinical environment, this device presents a critical disadvantage of complicated designs and measuring processes. As a result,

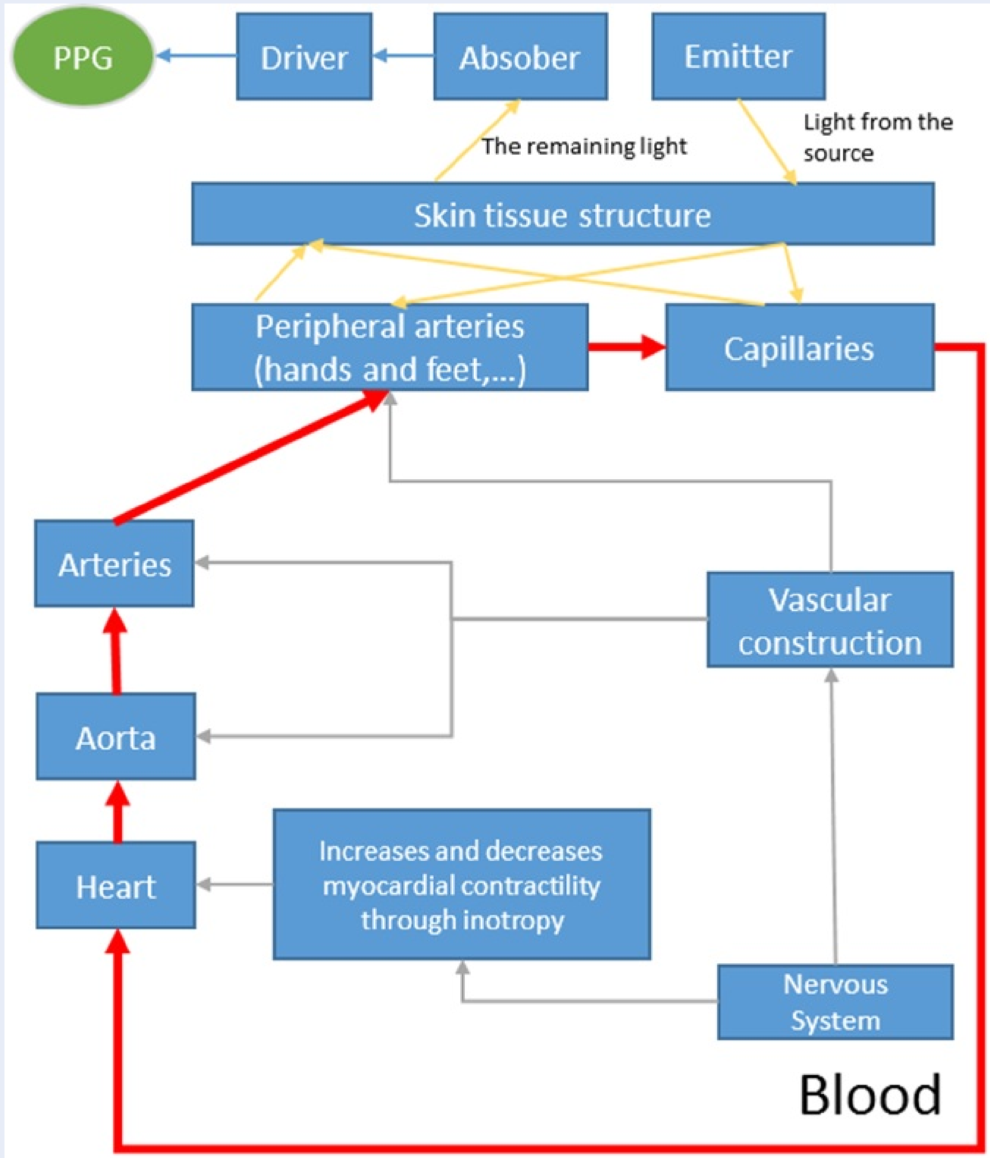

Figure 7: The PPG signal is the result of many factors.

obtaining a frequent schedule of monitoring is difficult, especially for patients who have difficulties in self-care, such as the elderly. This difficulty also applies to those who lack sufficient knowledge and skills to perform the measuring process and make necessary assessments of their health condition based on their blood pressure values.

The problems in measuring blood pressure seem to have been solved as studies,[16,17] pointed out similarities between the PPG signal and *arterial blood pressure (ABP)* as shown in Figure 13. PPG signal can be measured by a small, simple device and does not require any complex process. Besides, PPG devices integrated into smartwatches or other handheld devices enable more frequent measuring and can be based on a pre-programmed application. In addition, recorded data can be assessed by a machine learning or deep learning model to provide an early warning regarding blood pressure related issues that are dangerous to our health.

Currently, the measuring of blood pressure from PPG signal has been gathering more and more interest by researchers of a wide range of scientific fields from medical to digital-data processing, this has resulted in the introduction of many different algorithms. From a wide perspective, we can divide the studies into

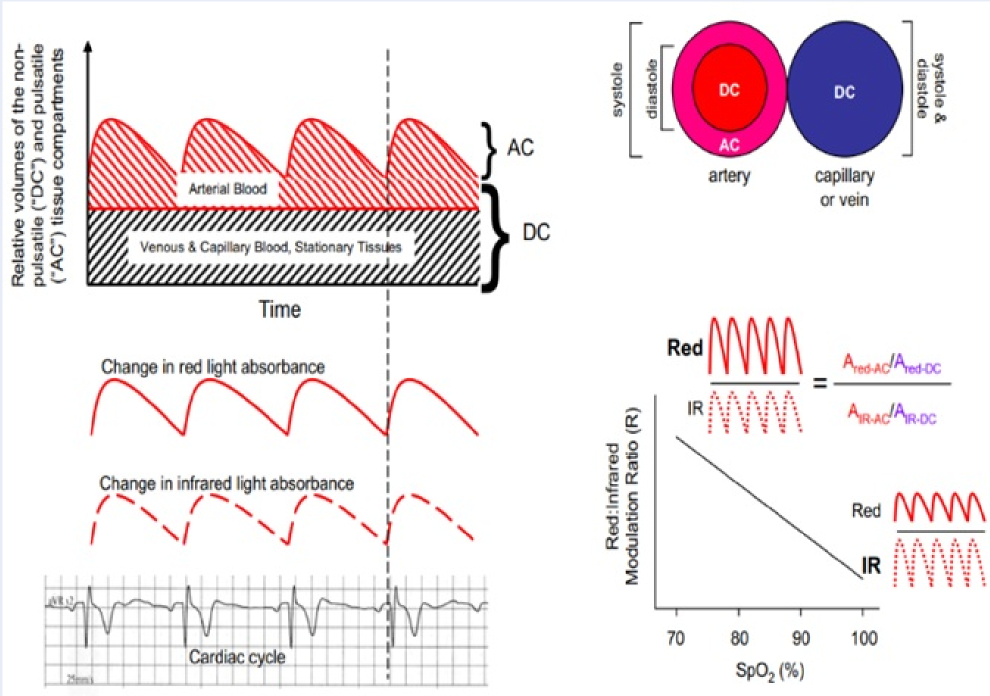

Figure 9: Correlation of SPO2 and PPG signal recorded from infrared and red light[6].

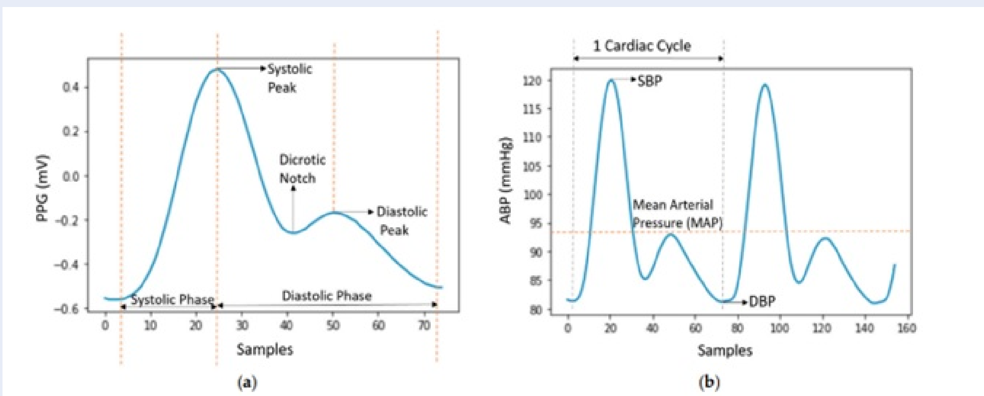

Figure 13: Similarities in morphology between PPG and ABP, (a) PPG signal, (b) ABP signal[18].

three main directions:

- Mathematical Model
- Machine Learning Model
- Deep Learning Model

Mathematical model provides formulas that calculate the blood pressure from distinctive variables extracted from the PPG signal. Among these variables, the most interesting ones are *pulse arrival time (PAT)* and *pulse transit time (PTT)*. PAT is defined as the amount of time for blood stream to reach a certain part of the body (arm, leg, ...) starting from the moment the ventricle contracts[19]. PAT is usually calculated by measuring the time from *electrocardiogram (ECG)* and PPG signal, Figure 14. Liang et al.[20] presents experimental results regarding the correlation of PAT and blood pressure, the experiments concluded that PAT is a potential index in monitoring blood pressure. Baek et al[21] applies a linear regression model to predict blood pressure through PAT, heart

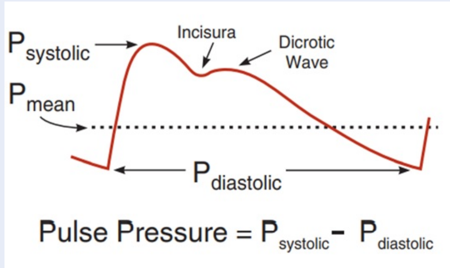

Figure 11: The blood pumped into the main arteries by the left ventricle creating a pressure which is transmitted in the from of a wave (Pressure pulse wave). The highest value of the wave is called systolic pressure, while the lowest value is called diastolic pressure[3].

Figure 12: Sphygmomanometers.

rate and arterial stiffness index:

$$BP = a + b * PAT + c * HR + d * T \quad (4)$$

Where, BP is the blood pressure value (SBP or DBP), HR is heart rate, TDB indicates arterial stiffness. Results of the model show a high value of correlation coefficient with the blood pressure, specifically, $R = 0.922$ for SBP, $R = 0.855$ for DBP.

However, we cannot always measure ECG thus replacing the ECG sensor with 2 PPG sensors positioned at two different places on the body, the resulting signal is called PTT. Studies surrounding PTT also pointed out that it is a useful index in estimating blood pressure[22,23].

Although PAT and PTT are considered to have a high correlation with blood pressure, these two indexes only serve to describe the transmission speed of the PPG signal. However, the relation between blood pressure and the PPG signal has much more to offer, specifically in its waveform. To elaborate on this topic, researchers have taken into consideration a set of PPG features combined with a machine learning model. A model of machine learning applied to estimate blood pressure from PPG can be shown in Figure 15. From the figure, *feature extraction* is the algorithm used for quantifying the required features from a raw PPG signal. The *feature selection algorithms* will help us determine the most useful set of features, while the machine learning model is tasked with the calculation of blood pressure from the input feature values. Typical features have been mentioned in the study of Chowdhury et al[24].

Many researchers have applied different machine learning methods as well as different sets of features to estimate blood pressure. After comparing 19 machine learning models combined with different feature selection algorithms, Chowdhury et al.[24] stated that the *Gaussian process regression* model along with the *Relief* algorithm showed the most accurate SBP and DBP values. The correlation coefficient calculated was 0.74 for SBP and 0.62 for DBP. Riaz et al[25] assessed the calculation results of blood pressure through a set of features including *rising time, falling time,* and *peak-to-peak distance*. In conjunction with the features, different machine learning models were applied and showed accuracy in calculations reaching 95%.

Despite the positive results, the accuracy of the PPG model (machine learning and feature selection) relies heavily on feature extraction and selection algorithms. To fix this issue, a deep learning model is also applied and has shown effective improvements. Figure 16 shows a flowchart describing a general process of applying deep learning in the calculation of blood pressure.

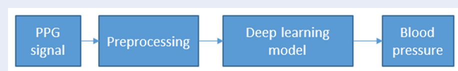

Figure 16: The process of applying deep learning in the calculation of blood pressure from PPG signals.

Instead of using feature extraction algorithms, the deep-learning network will automatically extract features directly from the raw PPG signal using *convolutional neural network (CNN)* or *recurrent neural network (RNN)*. These networks can be considered as an adaptive filter, they are trained to reach the lowest error possible. Hence, it will reduce the calculation as well as create a finer feature selection. Panwar et al[26] used a hybrid network called PP-NET to calculate SBP, DBP, and heart rate from the raw PPG signal. PP-Net was created from the combination of a two-layer CNN and a two-layer *long-short-term memory (LSTM)*, as shown in Figure 17. The CNN extracts the features from the initial PPG signal, while the LSTM (an RNN in nature) gathers all the results from previous calculations and combines them with

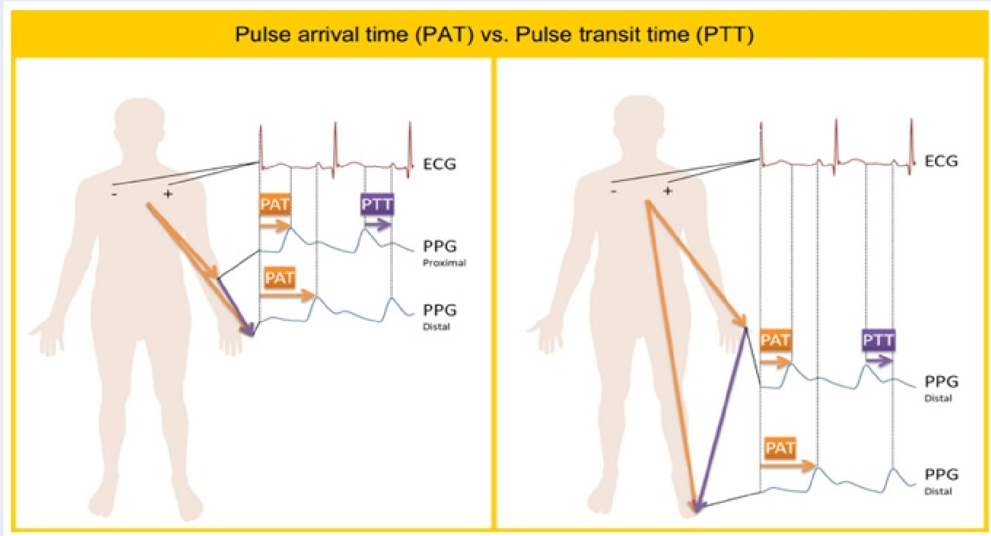

Figure 14: PAT and PTT [19].

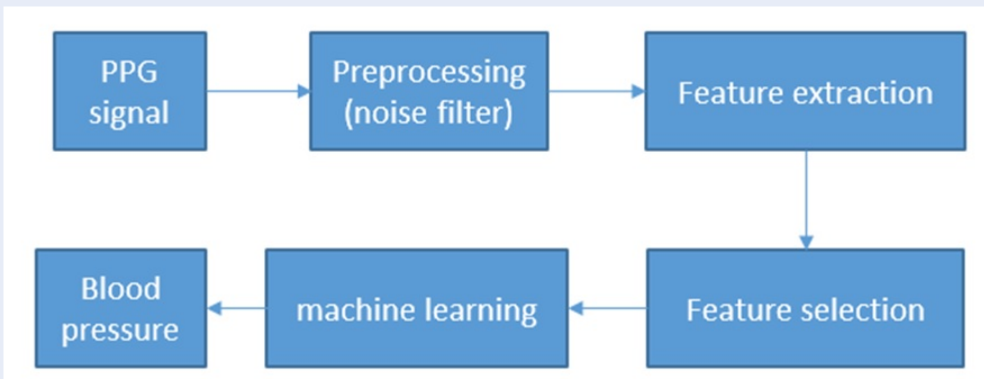

Figure 15: A summarized flowchart of "Blood pressure estimation using a machine learning model".

the new features' values to provide the most accurate results possible. The research provided a result with an error in calculations as follows: 3.97 mmHg for SBP, 2.30 mmHg for DBP. Besides, the calculation of SBP and DBP values, these deep learning models can also approximate the ABP from a raw PPG. Athaya et al [18] applied the U-Net, which is a combination of a CNN network and an autoencoder network. As previously mentioned, the idea of blood pressure calculation from PPG started from a high correlation between ABP and PPG regarding their form. In this research, the autoencoder network is applied to approximate ABP from PPG. After successfully recreating the ABP, the results of SBP and DBP have errors of 3.68 mmHg, and 1.97 mmHg respectively. Alongside U-Net, other networks are also researched for their capability to approximate ABP. Among them, Ibtehaz et al [27] showed that the use of MultiResUNet with a fairly similar structure to U-Net and also provided results qualifying for Grade A in the Bristish Hypertension Society standard [27].

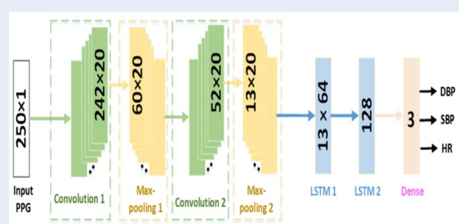

Figure 17: The structure of PP-Net [26].

Analyzing the pros and cons of this method, we can see that the deep learning method provides a far more accurate result at the cost of numerous calculations and high hardware requirements. Meanwhile, the other two methods can be easily integrated into mobile devices. To compensate for these difficulties, we can make use of wireless devices to send the data to a server to perform the calculations using deep learning models. On the other hand, the overuse of deep learning may also prove not as effective as expected when the mechanics and relations between PPG and ABP are still unclear. Thus, it would require a massive amount of data comprising various ages, health conditions, and demographics to address this issue.

In brief, the best option is to use deep learning as a tool to figure out the principles of PPG and ABP; From there, we can select models that best suit our needs to reduce the amount of calculations as well as optimizing applications and accuracy.

Cardiac arrhythmia

The contraction of the heart is performed by two types of cells: pacemaker and non-pacemaker. Pacemakers generate electrical signals that control the heart's contraction cycle, while non-pacemakers transmit the signals to the cardiac muscle cells. The transmission of signals among the cells is based on the principles of *depolarization* and *repolarization* of the cells. As long as depolarization and repolarization are stable, the heart can be considered healthy. However, if they are unstable, the heart will not contract normally, leading to a condition called cardiac arrhythmia. There are many types of cardiac arrhythmias, which are classified based on their frequency (fast or slow) or the location of the abnormalities (ventricle or atrium).

Cardiac *arrhythmias* affect the contraction of the heart, leading to changes in blood flow and blood pressure throughout the body. These effects can be expressed through PPG signals, and many studies utilize PPG signals to diagnose *arrhythmias*. The types of cardiac arrhythmia most studied are *atrial fibrillation (AF)*, *premature ventricular contractions (PVC)* and *premature atrial contractions (PAC)*. Sološenko et al [28] developed an application to detect PVC, combining a recursive least squares filter and a multilayer perceptron network to identify the exact moments that the PVC occurs in the raw PPG signal, Figure 18. This research's results have an accuracy of up to 99%. The AF, which is more dangerous than PVC, receives much attention from different researchers. Among the methods used, statistics applying the *root mean square of the successive difference (RMSSD) coefficient* and *Shannon entropy (ShaE)* on PPG signal can be considered the simplest one, [29–31]. Figure 19 describes a general process for AF detection based on PPG, where the RMSSD coefficient and ShaE are compared to a preset threshold to determine whether an individual is affected by AF This method has a sensitivity of 0.96, specificity of 0.97, and accuracy of 0.96 [29]. However, the range of the research is still limited, with only 76 participants [29]. Another existing problem with this research is whether the preset threshold is suitable for a larger sample size.

Besides statistical coefficients, a different approach to categorizing cardiac arrhythmias is to apply machine learning and deep learning models. Yang et al [31] categorized patients with positive/negative atrial fibrillation by using *a radial basis function kernel* and *support vector machine model* with inputs being extracted from the PPG signal, Figure 20, the accuracy of this method is also very high at 92.71 Furthermore, by comparing different sets of features, researchers concluded that the features extracted from the Haar wavelet for a 10-second piece of PPG signal are the best option. [32–34] utilized deep-learning networks to detect atrial fibrillation. The common

point of these studies is the stem network of CNN, which is also understandable as atrial fibrillation is related to changes in the frequency of PPG signals. Gotlibovych et al [32] combined CNN and LSTM to detect atrial fibrillation, and the study resulted in sensitivity = 0.99, specificity = 0.99. Another study [33], despite using only *a dense convolution neural network (DCNN)*, showed clear capabilities in diagnosing diseases other than atrial fibrillation, particularly, ectopy.

Moreover, a new approach was presented in [34], Figure 21, this study used a CNN to extract features and then applies multinomial regression to detect those patients with atrial fibrillations, the accuracy of this method is at 91.8%. This study suggests that adding signal features to a simple CNN network can improve the effectiveness of classification when the features help the CNN distinguish between signals with disrupted heart rhythm and noisy signals, which are difficult to differentiate using statistical or machine learning methods.

From the previous points, we can see that the application of PPG in the detection of many cardiac arrhythmias is a mutual interest of many researchers with a variety of methods. Despite the efficiency of each research being different, we are still unable to state which method is superior to the others. The differences in the research can be explained by the following factors:

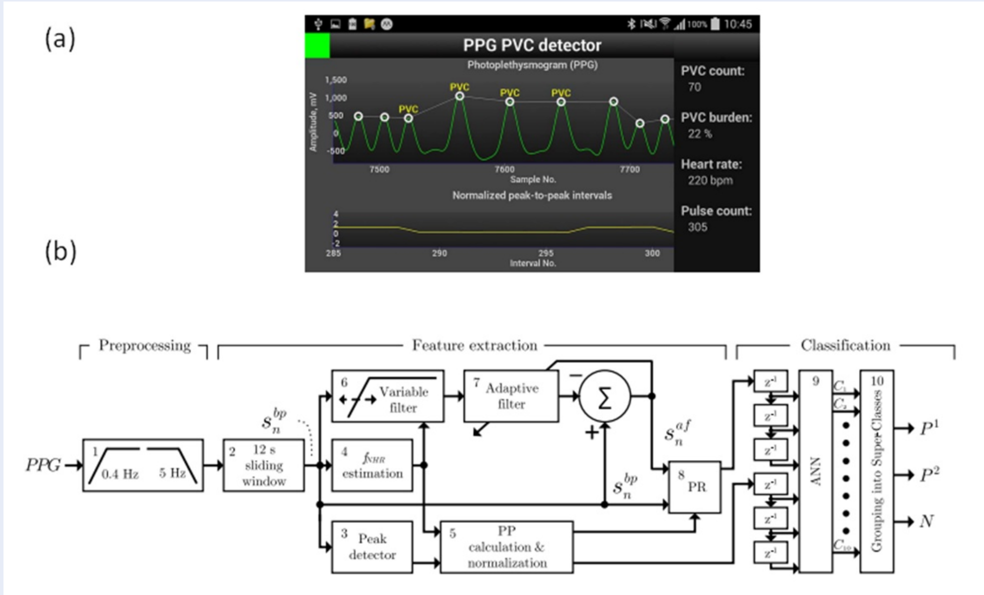

Figure 18: PVC detection algorithm and its application on an Android OS [28]. (a) The OS application of the algorithm. (b) The PVC detection algorithm has three steps: Preprocessing, which filters out electrical and apparent light noise. Feature extraction, which identifies the peaks in the PPG signal. Classification, which uses a multilayer perceptron network to classify the signal as normal or PVC.

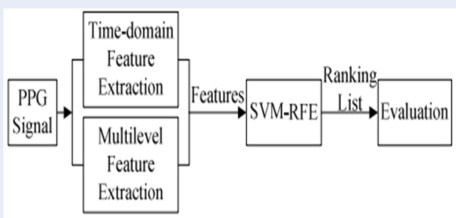

Figure 20: An Atrial Fibrillation Detection Algorithm [31].

- Difference in datasets regarding the sample size and their demographics.
- Differences in the pre-processings of data such as filtering and the length of the PPG signal being processed. This is due to the fact that cardiac arithmias only emerges in certain times of the day like for the case of PVC, or they might not manifest too clearly in the early stages of the disease.
- Studies do not specify the effect of each disease on the change of PPG signal, thus limiting the accuracy of when several different diseases will have similar manifestations.

Vessel wall aging

A PPG signal comprises many factors in the circulatory system, of which the vessel wall plays a crucial role. A vessel is composed of three layers, as shown in Figure 25. The *Media layer* contains *smooth muscle cells with molecules of collagen* and *elastin*. These *smooth muscle cells* can stretch by the control of the *autonomic nervous system* to change the diameter of the vessels, enabling the regulation of blood flow to the organs. Elastin and collagen work together to create the elastic feature that can be found in our blood vessels. Their concentration determines how elastic the vessels can be. This structure of the vessels makes the vessel system an elastic system that controls the flow or transportation of blood throughout the body, thereby affecting the PPG signal. Therefore, we can conclude that the PPG signal can also provide predictions regarding the status of blood vessels. There have been many studies related to this topic, [35–37], which have identified connections between PPG signals and the aging of blood vessels by providing the following criteria:

- The stiffness index (SI), Figure 22, is calculated by dividing the amplitude h of a PPG signal by the amount of time, ΔT_{DVP}, between two peak of PPG wave [38].

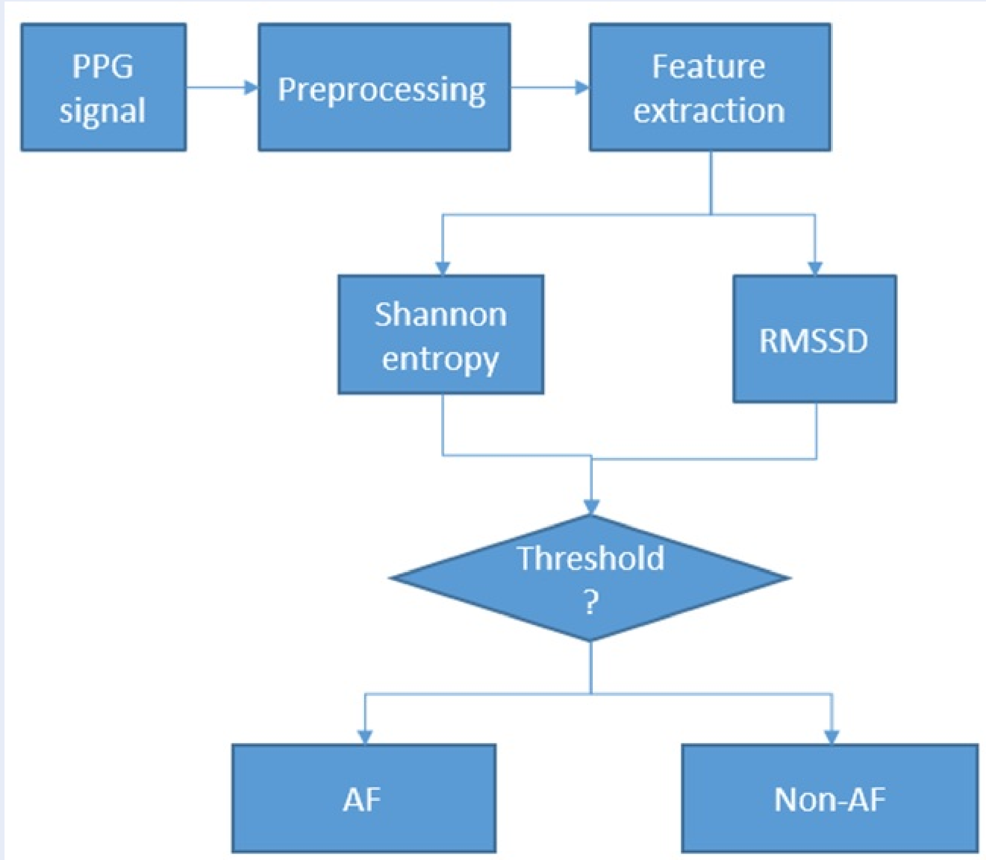

Figure 19: A common process of an algorithm applying RMSSD and ShE to detect patients with atrial fibrillation.

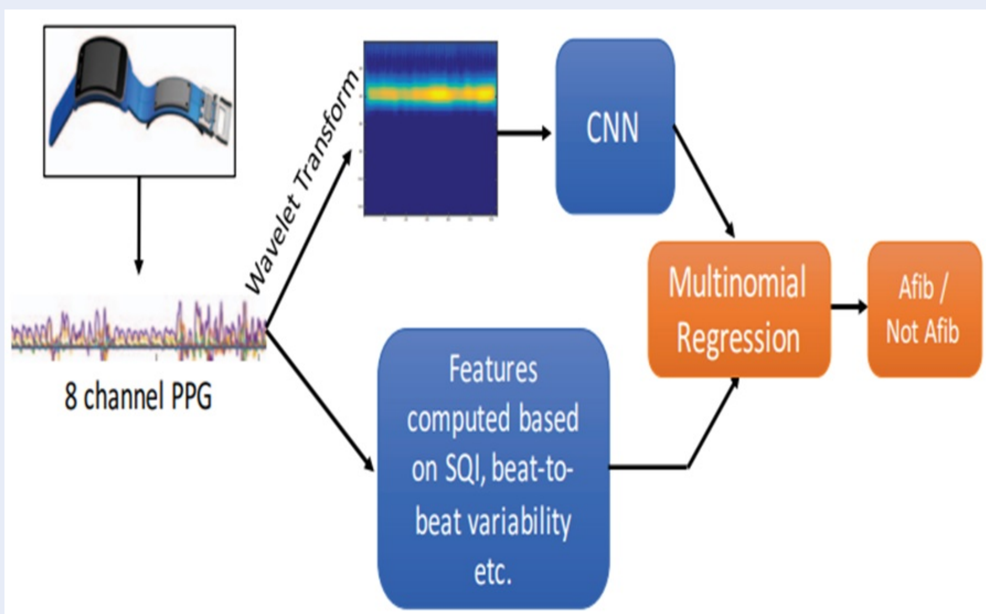

Figure 21: The CNN network transforming wavelet and extracting features in detecting atrial fibrillation [34].

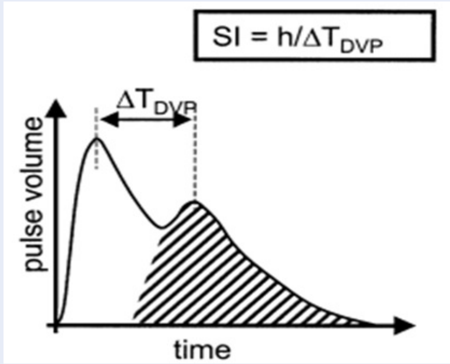

Figure 22: The stiffness index [39].

- *The inflection and harmonic area ratio (IHAR)*, Figure 23. This index is used to monitor the peripheral perfusion status [39] and can be calculated from the area of the lower side of the PPG wave and from the height of peaks in the Fourier spectrum [39].

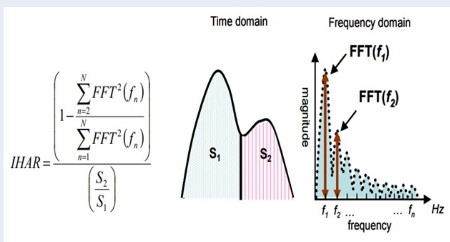

Figure 23: The inflection and harmonic area ratio applied to monitor the status of peripheral perfusion [39].

- *The aging index*, Figure 24, is calculated from the height of the peaks in the 2^{nd} derivative of the PPG signal [40].

The research on indexes used to assess the status of blood vessels is based on experiments and knowledge of their structures. These indexes are exceptionally useful and convenient in providing a quick and overall evaluation of the vessel's condition. However, their limitations lie mostly in the fact that they rely solely on statistical tools, thus being limited to providing descriptions of symptoms without any meaningful conclusions.

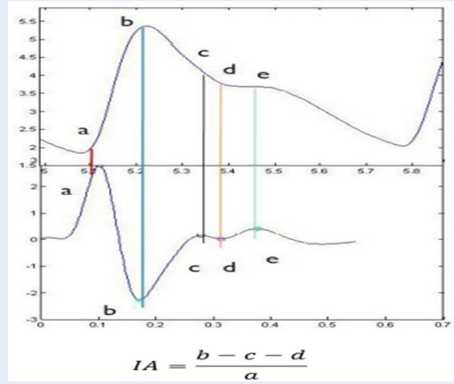

Figure 24: PPG (upper) and its 2nd derivative (below) [40].

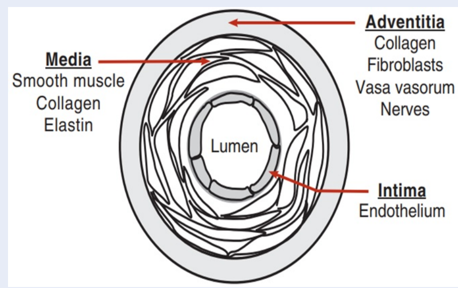

Figure 25: Structure of a blood vessel [13].

DISCUSSION

Based on the material above, we can see that other than the public applications and tools to monitor health conditions or the clinical diagnosis of SPO2 and heart rate, PPG signals can also be used in estimating blood pressure, detecting cardiac arrhythmias, and estimating blood vessel aging. This has opened tremendous potential in remote health monitoring using only a small, compact device and contributed partly to solving the overload issue that many hospitals are facing. Moreover, the advantages of a compact, optimized design combined with the new trend of *IoT (internet of things)*, the patient's health conditions can be monitored constantly, which in turn creates many benefits.

First of all, for patients who are affected by cardiovascular diseases such as high blood pressure and heart disease, the probability of a stroke is more imminent. These sudden strokes can be foreseen by signs such as changes in blood pressure and heart rates [41]. With constant PPG monitoring devices that can detect these abnormal signs and issue warnings, we can take precautions in case of worst-case scenarios when a patient is unconscious. Warnings and alarms from these devices may prove vital for the necessary emergency services to be carried out in time.

Secondly, the modern lifestyle we lead makes us more susceptible to diseases that are often related to our lifestyle[42]. These diseases progress over time and gradually accumulate, and their effects may only become apparent when they have already become fatal. A possible solution is to monitor our vitals more frequently, such as blood pressure, heart rate, and vessel aging, in order to receive early warnings. This solution can be made possible and easily accessible through the use of wearable PPG devices. These devices can collect data, calculate continuous vital signs, and process them using an algorithm. The results can then be sent to a healthcare professional for assessment and possible early warnings. Based on these early warnings and the doctor's consultations, users can make timely adjustments to their lifestyle to improve their condition.

Lastly, the data of the users' or patients' treatments can be stored in a database where it can be actively and continuously updated. This serves two important purposes: for those who are under treatment, doctors can keep their patients under constant surveillance to detect unexpected events or make adjustments to the treatment regimen that are not possible with traditional periodic tests. Furthermore, the patients' data, which are constantly updated, will contribute greatly to the development of our medical fields.

But, there have also been many obstacles to the PPG method, some that need to be consider is:

- The data
- The sensitivity to noise of PPG
- The research method

The data sources for researching the efficiency of PPG are still limited and unsynchronized. Studies on PPG signals are often conducted in European-American regions, which makes the database unable to represent all demographics worldwide. Although open sources of PPG signals exist, such as MIMIC[43], the consistency of these data sources is not assured due to the lack of standards for sampling processes or devices. Additionally, the sampling of PPG signals conducted by researchers is often limited due to legal matters, resulting in unreliable sample sizes in many places, with many occasions where only 200-300 samples are taken.

The PPG signals can easily be corrupted by noise or other environmental factors,[44]. Despite the advantages of compact, mobile designs, easy operation, and high information content, PPG signals can only provide useful results under stable operating conditions, meaning users must be in a relaxed and well-rested state. Hence, it is difficult to maintain constant surveillance when daily activities require physical motion, leading to often mistaken signals between noise and useful signals. There are two main trends in PPG signal processing, , namely "noise detection - removal" and "restoration of noisy signal segments". The purpose of noise detection and removal is to identify PPG signal segments that are corrupted by noise and remove them from the signal. The main method used in this trend is to use quality evaluation indices. The signal segments are divided into smaller window segments that can overlap or not, and then quality evaluation indices are calculated for each window segment. Window segments with indices outside the acceptable range will be considered as noise and removed. Commonly used indices include skewness, kurtosis, and standard variation.

For the approach of restoring noisy signal segments, in addition to detecting noisy segments, algorithms also restore the noisy signal segments. There are many methods used, such as using Kalman filter[5], ICA[45], machine learning[46], … The common point of these methods is the use of a reference signal, usually an accelerometer sensor. The accelerometer sensor records changes in acceleration during user movements, from which the algorithm will combine with the raw PPG signal to obtain a signal without noise.

Currently, it is impossible to conclude which approach is better because they are used depending on each application. For PPG applications in calculating blood pressure and diagnosing arrhythmias, the removal of noisy signal segments is used more because these applications require intact signals, while the other approach is suitable for applications that only use a few characteristics of the PPG signal such as heart rate and SPO2 calculation. A famous algorithm that uses the PPG signal to calculate heart rate when the user is moving is the TROIKA algorithm[47].

While there has been a great deal of research conducted on PPG signals, many of the methods used rely heavily on data-driven approaches, without fully exploring the underlying nature of the PPG signal itself. This can be attributed to the fact that the PPG signal is complex and contains a wealth of information and features, making it challenging to understand exactly what these features can tell us about changes in our health. As a result, there is still much to be learned about the potential of PPG signals, and how they can be used to improve our understanding of human health and wellbeing..

PPG research has encountered multiple challenges, primarily due to inconsistencies in data collection and processing, leading to an incomplete understanding of the nature of PPG signals. To overcome this issue, there is a need for a standardized process for PPG data collection and processing. This would include agreeing upon a set of standards for the devices used to collect PPG data and recording detailed information about the participants.Most studies have focused on data-driven methods to analyze PPG signals, without considering the complex interactions of the organs in the body that contribute to the signal. To address this, researchers have adopted two approaches: actual sampling and simulation modeling of PPG signals. Simulation modeling of PPG signals is particularly useful in monitoring and isolating different factors that contribute to the signal, without violating medical legal regulations. Furthermore, simulations can be used to test theories and compare the results to actual PPG data for reference. By combining these approaches, we can gain a more comprehensive understanding of the nature of PPG signals and how they can be used to inform clinical practice. This will require collaboration between researchers to develop a standardized approach for PPG data collection and processing, as well as continued exploration of both actual sampling and simulation modeling techniques to gain a more in-depth understanding of PPG signals.

CONCLUSION

In a nutshell, PPG is a technology of great value not only for informative health monitoring, but also for making the idea of remote health-check and online hospitals more and more realistic. In order for developments in PPG signals to advance, the problems mentioned in this paper must be addressed. With technological improvements in materials science and semiconductors, these difficulties should not obstruct progress for too much longer. Morever, to overcome the current limitations of PPG technology, a multi-light wave and sensor system can be employed to gain more comprehensive health information, rather than relying solely on a single light wave or sensor. This trend is gaining traction in the efforts to expand the implementation of PPG signals in practice. For example, Sjoerd Rozendal has introduced a new technology that can scan the vein of a finger by using PPG signals with an emitter consisting of a series of infrared LEDs and an absorber, which is an image sensor (CCD camera)[48]. Furthermore, The Medical Futurist company has developed a device called the Vein scanner[49], which is capable of scanning the veins under the skin, proving to be extremely helpful in medical tasks. The continued evolution and application of PPG technology will lead to even more significant advancements in remote health monitoring and online healthcare services.

ABBREVIATION

PPG: Photoplethysmography
ECG: electrocardiogram
ABP: Arterial blood pressure
SBP: Systolic blood pressure
DBP: Diastolic blood pressure
SPO2: Saturation of peripheral oxygen
CNN: Convolutional neural network
LSTM: Long short term memory
RMSSD: Root mean square of successive differences
AF: Atrial fibrillation
PVC: Premature ventricular contractions
PAC: Premature atrial contractions
DCNN: Dense convolution neural network

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COMPETING INTERESTS

The authors declare no competing interests associated with the publication of this article.

AUTHOR CONTRIBUTION

Thanh Tung Luu, Khanh Duy Phan: methodology, analysis, Duy An Huynh: supervision.

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Bài tổng quan

Tín hiệu PPG và ứng dụng trong lĩnh vực y tế

Phan Khánh Duy, Lưu Thanh Tùng*, Huỳnh Duy An

TÓM TẮT

Thăm khám sức khỏe từ xa đang trở thành một xu hướng đang nổi lên trong lĩnh vực chăm sóc sức khỏe, nhằm giải quyết vấn đề quá tải bệnh viện và tối ưu quy trình theo dõi sức khỏe của bệnh nhân. Để đạt được những mục tiêu đáng khen ngợi này, một thiết bị có khả năng trích xuất các chỉ số sức khỏe quan trọng là vô cùng cần thiết. Vấn đề này có thể được giải quyết bởi các thiết bị sử dụng công nghệ photoplethysmography (PPG) bởi sự nhỏ gọn, dễ sử dụng và cung cấp nhiều thông tin liên quan đến sức khỏe. PPG là một phương pháp không xâm lấn dùng để đo sự thay đổi trong lưu lượng máu dưới da bằng cách ghi lại sự thay đổi cường độ ánh sáng đi qua da. Kỹ thuật này có rất nhiều ứng dụng, bao gồm đo mức bão hoà oxy trong máu, ước tính áp lực máu, đánh giá quá trình lão hóa mạch máu và phát hiện loạn nhịp tim. Do đó, công nghệ này sẽ mở ra một tương lai đầy hứa hẹn trong việc giải quyết vấn đề quá tải ở các bệnh viện. Bài báo cung cấp một cái nhìn tổng quan về công nghệ photoplethysmography (PPG), trình bày các nguyên tắc cơ bản và nhấn mạnh các ứng dụng đáng chú ý của nó. Cụ thể, bao gồm ứng dụng của PPG trong đo mức bão hoà oxy trong máu, ước tính áp suất máu, đánh giá sự lão hóa mạch máu và phát hiện loạn nhịp tim. Bên cạnh những ứng dụng vô cùng hữu ích, PPG vẫn còn một số vấn đề cần được giải quyết, chẳng hạn như sự hạn chế về tập dữ liệu PPG đối với một số nhóm dân số cụ thể, sự nhạy cảm của tín hiệu PPG đối với chuyển động và điều kiện môi trường, và thiếu rõ ràng về bản chất của PPG dẫn đến việc thiếu tiêu chuẩn trong việc lấy mẫu và giải thích cơ chế tác động của PPG trong các ứng dụng của nó. Và vấn đề này cũng được bàn luận trong khuôn khổ của bài báo.

Từ khoá: tín hiệu photo-plethysmography, ứng dụng của tín hiệu photo-plethysmography, nguyên lý của tín hiệu photo-plethysmography

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