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From Signal Acquisition to Signal Processing Methods in Photoplethysmography Technology: Applications, Comparative Analysis, and Future Perspectives

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Abstract. Photoplethysmography (PPG) is a popular, non-invasive method often used to keep an eye on heart health by tracking subtle changes in blood flow. In this paper, we offer an in-depth overview of the current state of PPG technology. We start by describing how signals are captured and processed, then discuss how these techniques translate into everyday use. We look closely at various measurement methods, carefully comparing their effectiveness. Along the way, we point out common issues like interference from body movements and unwanted environmental noise, both of which often disrupt accurate readings. To address these challenges, we cover several practical solutions, including smarter filtering techniques, multi-color light analysis for clearer signals, and recent approaches involving machine learning. We also acknowledge persistent difficulties, such as why different people often get inconsistent results and how complicated biological factors can make readings less reliable. Looking toward the future, we explore promising developments, including systems that combine data from multiple sensors, round-the-clock health tracking capabilities, and health tools tailored to each individual's needs. Ultimately, our goal is to present a clear summary of today's PPG technology, while encouraging fresh thinking and innovation in the field of wearable health devices.

Keywords: Photoplethysmography, Signal Processing, Motion Artifacts, Machine Learning, Wearable Devices

1. Introduction

Photoplethysmography (PPG) is an optical method widely used to check on heart health without needing direct contact with the body. It works by shining light into the skin and then analyzing how that light is absorbed or scattered, reflecting tiny changes in blood flow beneath the surface. By carefully tracking these slight variations, it's possible to measure important health indicators like heart rate and blood oxygen levels in real-time. As more people start using wearable health devices and online medical consultations become common, it's becoming crucial to improve the ways we process these PPG signals, especially to overcome issues like interference from movement or surrounding environmental factors.

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This review takes a close look at current methods for processing PPG signals, highlighting how effective each method is at dealing with common problems, such as distortions caused by motion and unwanted noise from the environment. By comparing different techniques side-by-side, we can clearly see their advantages and limitations. Beyond this comparison, the paper also explores new, exciting directions in research, such as using multiple colors of light to gather more detailed information, combining different kinds of sensors to improve accuracy, and applying artificial intelligence techniques to better understand and interpret the data. These developments show great promise for making PPG-based wearable devices even more useful in delivering personalized healthcare.

2. The principle of the PPG

2.1. working principle of PPG

Photoplethysmography (PPG) is a tech that base on light processing. The light is emitted by a light source (such as LED); after interacting with the issue in human body, a photodetector would receive the light which is been reflected or went through target skin. The whole process is to illustrate how the blood volume changed in vessel by the time. The information is essential to figure out the vital signs of patient or wearable device owner [1,2].

Signal of PPG is mainly acquiring by two methods: Reflection and Transmission. Transmission often used in the issue which is thin enough for a weak light to transmitting over. Earlobe and fingertip are the ideal target. Reflection is much more popular in industry; the reason is current wearable device are mostly watch and wrist is too thick for the light from LED to transmit. In those situation, light emitter and detector was in the same side to work out how many lights was absorbed by the skin issue. Furthermore, neck is another part which frequently used Reflection method [3].

In the procedure of acquiring the PPG signal, the skin and some other issue inside show the consistent in processing the light emitted by LED, since they keep still in most of the time. However, the vessel shows a different characteristic, its way of processing light changes regularly over time. The reason is blood volume in vessel changed with each heartbeat. This special characteristic suggests a methodology to find out the rate of heartbeat. More specifically, when target user heart pumps blood during the systole phase, the blood volume increase, and that would lead to less light bounces back. Vise versa, during the diastole phase, and there is less blood, more light would detect. These change of light intensity result in a wave pattern that indicated heart rate. Additionally, another vital sign related to blood volume for instance, oxygen level could be found out as well [4].

PPG technology faces challenges due to the variability across different body parts. The earlobe is ideal for transmission mode, whereas the wrist or forehead are more suitable for reflection mode. The efficiency of light travel or reflection depends on blood flow and tissue thickness [5].

However, there are interferences. Movement and light from the environment can affect PPG signals. Movement artifacts typically occur when user doing sport, the sensor would shift relative to the skin, and the light detector receive is not the light emit from the LED. In addition, ambient light interferes the amount of reflected light as well [5]. These interferences vary by body location; wrist signals are more susceptible to movement artifacts, while earlobe or fingertip signals are less affected due to the easier fixed device [6].

There are some methods which is already devised in this industry to refine the signals despite these interferences. One approach is to adjust the wavelength of LED, such as using green light, to

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reduce certain types of interference [5]. Additionally, signal processing techniques are employed to eliminate constant and motion-related signal components, enhancing signal accuracy [5].

2.2. Accuracy and efficiency in signal acquisition

Acquiring PPG signals with high precision and improving power efficiency is essential for the technology's performance and reliability. Precision ensures that the signal accurately reflects the changes of vital signs of user, while power efficiency impacts device battery life and user experience, particularly for extended use. Increasing precision reduces noise, yielding clearer physiological data. Improving efficiency prolongs battery life, which is crucial for portable devices.

In this section, some strategies which aim to enhance the accuracy and energy efficiency of PPG signal acquisition would be discussed.

2.2.1. Accuracy

Advantages of Green Light Sources: In PPG procedure, green light stands out for its signal quality and interference resistance. Unlike red and infrared light, green light penetrates less deeply into the skin, capturing blood volume changes in superficial vessels with minimal noise from deeper tissues [1]. Red and infrared light, which penetrate deeper, are more susceptible to interference from deep veins and tissues, potentially distorting the signal. Another benefit is that there is less green light in the environment, which indicated that the device can reduce interference with ambient light to improve accuracy. This view will discuss later [5].

Accelerometer-Assisted Motion Artifact Reduction: Motion artifact is a common challenge in PPG signal acquisition. However, integrating an accelerometer could monitor the device's movement in real-time, aiding in the prediction and mitigation of motion's impact on the signal. The accelerometer provides motion data which is helpfully to identify the direction and intensity of motion artifacts, which can then be addressed with some specifically design algorithms [5]. Combining an accelerometer with adaptive filtering can substantially decrease noise caused by motion, thereby increasing the precision and reliability of PPG signals [5].

Interference Reduction Using Multi-Wavelength Approaches: Employing multiple wavelengths is pivotal in mitigating various interferences in PPG readings. By analyzing data across different wavelengths, such as green and red light, the environmental light interference can be identified and addressed. If a green light source is causing disturbances, the green LED signal will exhibit more noise, but the red light, less affected by green interference, can provide a clearer signal. Conversely, green light is less impacted by red light interference. Utilizing diverse wavelengths allowing cross-verify and minimize ambient light interference, thereby enhancing measurement precision [2].

Improved Accuracy Through Faster Signal Processing: Certain PPG devices incorporate hardware that expedites signal processing. These components can swiftly handle high-frequency sampled data, reducing latency and preventing errors associated with delays. For example, adaptive predictive filtering can eliminate noise in real-time and improve the signal-to-noise ratio, ensuring our measurements are highly accurate [5].

2.2.2. Efficiency (power efficiency)

In the usage of PPG technology, power efficiency is crucial for user experience, particularly for continuous, long-term monitoring. Reducing power consumption extends battery life, which is essential for portable and wearable devices and it would bring a much wider usage scenario.

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Reducing LED Drive Power Consumption: The power draw from LEDs is a significant factor in battery depletion in PPG devices. To alleviate its effect, adaptive light intensity control can be employed to modulate LED brightness in response to ambient light levels, conserving power without compromising signal integrity. The screen light controlling strategy is an existing scheme that can be used for reference [2].

Reducing Power Consumption of Signal Reception Sensors: Enhancing power conservation can also be achieved by optimizing the efficiency of signal reception sensors. This includes selecting low-power photodetectors and using more efficient circuitry to handle digital signal. By opting for designs with lower voltage and current requirements, a substantially sensor power usage can be reduced [5]. However, it may result in a lower signal-to-noise ratio, because of less attention in accuracy. Additionally, low-power designs might restrict the ability of our signal processing circuits to handle significant signal variations, which could affect heart rate measurements and the other physiological parameters detection. However, this method is recommended for those target user who pay little attention to accuracy [2].

2.3. Comparison of methods for improving accuracy and efficiency

This section compares various methods employed to enhance the precision and energy efficiency of PPG technology. Evaluating the strengths and weaknesses of each technique provides insight into their suitability and limitations across various applications.

Accelerometer-Assisted Motion Artifact Reduction vs. Software Filtering:

Minimizing motion artifacts is vital for PPG technology. Traditionally, ECG has been the solution for precise physiological data, but it's costly and requires skin-contact electrodes, which might be uncomfortable. In contrast, PPG offers a non-invasive, safer, and more user-friendly option. However, motion artifacts can interfere the accurate acquisition of PPG signal, particularly during moving situation such as doing sport [5]. Effective mitigation of motion artifacts can largely widen the applicability of PPG in scenarios demanding precise physiological insights.

Accelerometer-assisted motion artifact reduction located and corrects artifacts by tracking movement direction in real-time, through the accelerometer. This method stands out in dynamic settings, such as during exercise or health tracking, where movement is frequent [5]. Conversely, pure software filtering using specifically design algorithm to diminish artifacts. It performs well with simple movements and better power efficiency but struggles with complex or frequent motion scenarios [5].

Green Light vs. Red and Infrared Light:

The choice of light source in PPG applications varies based on their benefits and drawbacks. For surface tissues like the wrist, green light, with its moderate penetration, captures blood volume changes effectively while minimizing interference from deeper tissues, offering high accuracy [1]. In regions like the earlobe, where transmission-based measurements are prevalent, red and infrared light, with their deeper penetration, can efficiently capture transmitted signals, especially in thin tissues [5].

However, red and infrared light can be more prone to interference from venous blood and deeper tissues in other scenarios. In addition, more light in the environment are likely to interfere red light, which increasing signal noise, particularly with reflective measurement techniques. Green light outperforms in these cases due to its superior signal-to-noise ratio [5].

Multi-Wavelength Techniques:

It could describe as A Double-Edged Sword. In principle, it act as a sophisticated filter, distinguishing between genuine physiological signals and background noise. By correlating data

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from various wavelengths, they can effectively identify and mitigate external light interference, enhancing accuracy in challenging lighting environments [2].

Yet, there's a downside: these techniques can consume significant power. Operating multiple light sources and processing the signals places a burden on battery life. Consequently, in scenarios where power conservation is critical, multi-wavelength approaches may not be the most suitable option [2].

Hardware Enhancements, Dynamic Light Intensity vs. Adaptive Sampling:

Dynamic light intensity control operates similarly to adjusting mobile phone—by lowering LED brightness in response to ambient light levels, it conserves power without compromising signal integrity [2].

Adaptive sampling techniques is a solution that reducing overall sampling frequency by only sampling at key moments, thus lowering power consumption. Both methods are highly effective and can be used in conjunction. In some scenarios, more advanced scheduling strategies can further optimize the combination of these two techniques to lessen their limitations, such as balancing light intensity adjustment and key sampling timing in complex scenarios [5].

Hardware Acceleration Modules:

These modules would significantly improve signal processing speed and accuracy; this advantage is addicted to those people who require highly accurate physiological information. This method acts as a turbo charger for signal processing. These modules swiftly process data, ensuring that vital physiological parameters like heart rate and blood oxygen levels are accurately monitored. They are irreplaceable in scenarios where precision is priority, such as in medical and professional athlete monitoring, where the priority real-time detection [5].

3. Comprehensive analysis of signal processing techniques in PPG

3.1. Significance of PPG signal processing

To record the PPG signal, a non-invasive photoelectric conversion technique is employed. Light will travel through human tissue, including muscle fat, venous blood, skin, and other reasonably stable tissues, when the body is exposed to an external light environment. The rate at which light is absorbed is also pretty constant. However, the human circulatory system has an impact on another feature of light during irradiation. The heart's regular beats cause the arterial blood to pulse and alter periodically, which affects how much light is absorbed. A pulsed signal is produced by the fluctuations in blood volume that occur with each heartbeat. After detecting this light from the body, photonic converters use a variety of circuit designs to convert it into an electrical signal that matches the regular pulsations of the heart. The PPG signal is the name given to this signal, which represents arterial blood beats as a result of variations in vascular content.

Although pulse waves contain a multitude of physiological information about humans, the waveform map that is gathered only shows the most fundamental morphological characteristics, failing to capture the important information that is present in the pulse wave signal. Therefore, a more in-depth examination and interpretation of pulse waves is necessary. The signal processing techniques now employed in pulse waves can be divided into three categories: frequency-domain, time-domain, and time and frequency domain analysis.

3.1.1. Frequency-domain analysis method

The frequency domain analysis method is a processing and analytical approach that depends on the features of frequency domain signal variations. In order to obtain frequency domain information and

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enable additional analysis of the pulse wave signal, this usually entails frequency domain modifications. It is feasible to derive physiologically significant information from the frequency spectrum by looking at the pulse wave's amplitude and phase fluctuations in the frequency domain. A popular method for signal frequency domain analysis is the Fourier transform, which allows pulse wave signals to be converted from the time domain to the frequency domain and so reveals the frequency domain properties of the signal. They may reflect the frequency component and frequency distribution law of the signal and perform quantitative analysis of the signal, including the main frequency component, frequency range, and power spectrum of the pulse wave.

In addition, the frequency domain analysis approach may eliminate interference and lower signal noise, improving the accuracy and quality of the data. However, we have specific needs for the signal processing and analysis technology in the processing process, and the frequency domain analysis method's required signal transformation may result in the loss of certain signal information. This approach requires more technical know-how and is more complicated than the time-domain analysis method. We can determine the energy distribution of various pulse waveforms in the frequency domain and obtain feature values of additional dimensions through frequency domain analysis; however, further investigation and validation are required to determine the relationship between various frequency domain features and physiological data.

3.1.2. Time-domain analysis method

Pulse wave is a periodic sequence of time-changing waveform signals that continuously changes with the human heart beat. In addition to the fact that the time domain analysis features include peak, area, slope, and pulse wave related information, it is not necessary to use complicated

mathematical tools for processing and comprehensible, useful, and combined with pulse wave-related knowledge.

The system can determine the physiological characteristics, the significance of waveform parameters, and the rules for analysis and adjustment of the underlying pulse wave signal qualities. Processing temporal domain analysis in clinical practice is a rather quick process that can yield useful elements from the temporal dimension that accurately reflect human state and signal processing capacity. Nevertheless, the tool has limits; it can only extract the temporal signal's features and offers a limited amount of information, making it impossible to completely display the signal's characteristics. Therefore, to increase the effectiveness of signal feature use, time-domain analysis typically has to be integrated with other analytical techniques.

Reliable information can be recovered even in somewhat noisy surroundings thanks to time-domain analysis's comparatively low requirements for signal sampling frequency and signal-to-noise ratio. There is a lot of useful physiological information in the pulse wave, but it cannot be fully described by features in a single dimension. Additionally, noise will also affect feature points in the time domain, making feature extraction more challenging. Only a few fundamental characteristics of the pulse wave signal can be extracted using time domain analysis; in-depth frequency domain information about the signal is not possible. As a result, the pulse wave signal's impact from basic time domain analysis is only at a limited level.

3.1.3. Time and frequency domain analysis method

Frequency domain and time domain investigations are combined in time frequency domain analysis. Information can be extracted from both the time and frequency domains by accounting for the features of these two dimensions. When compared to time or frequency domain investigations alone,

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this approach provides a more thorough and precise knowledge of the properties and patterns of pulse wave signals.

Wave signal analysis is a potent tool for analyzing non-stationary pulse wave signals and offers a distinct benefit. The wavelet transform and the short-time Fourier transform are two methods that are commonly used in time-frequency domain analysis.

Nevertheless, the short-time Fourier transform has the drawback that the correctness of the procedure depends on the length and appropriateness of the window function. The effect of signal analysis also depends on the accuracy of the window function, and the window size must be reasonably high in order to adjust to the change of various frequency components.

The wavelet transform, on the other hand, can offer superior frequency over temporal and short-time resolution. Better frequency resolution is made possible by the wavelet transform, which uses a collection of wavelet basis functions with varying scales and placements to analyze various frequency components at various scales. On the other hand, wavelet basis functions are local and can assess local signal changes, which allows them to provide superior temporal resolution.

By using the wavelet transform, it is possible to deal with non-stationary signals more clearly. Moreover, the wavelet transform cannot select the window function like the short-time Fourier transform as the wavelet basis function is fixed. By doing this, the issue brought on by the short-time Fourier transform's improper window function selection is avoided, and the wavelet transform is also made more practical and simpler to apply.

The time-frequency domain analysis approach, as opposed to frequency domain analysis, maximizes the utilization of both time and frequency domain data while minimizing the loss of signal information. This makes it possible to extract the characteristic information from pulse wave signals more thoroughly, leading to more accurate and trustworthy assessments. As a result, it provides physicians with more accurate physiological characteristic data.

3.2. Character of different method of signal processing

3.2.1. Peak detection

According to most researches, peak detection methods are effective in capturing valuable information from the images. There are two main stages contained in peak detection method: preprocessing and envelope detection and peak determination.

3.2.1.1. Preprocessing

One of the most important phases in the PPG peak detection task is preprocessing.The goal of this step is to exclude components that do not reflect the feature of interest(e. g., heart rate and heart rate variability). Various filtering techniques, such as low pass, adaptive, high pass, singular value, and pattern decomposition, can be employed in the preprocessing step to reduce HF noise and baseline distortion. This technique makes the PPG signal more apparent in the systolic peak fraction. The noise transcendence stage likewise heavily relies on the moving average filter. For instance, a three-point bidirectional moving average has been suggested in certain studies to remove the filter-induced phase delay. By removing these two processes through filtering and noise, the researchers in the most recent study suggest a novel way to lessen the influence of noise. To make the signal smoother, a three-point moving average filter is applied.

To assist additional analysis, the entire signal is divided into many noise removal components, and significant features including standard deviation and inclination are computed. The threshold is

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then set and the segment that exceeds it is removed based on these characteristics. In the final step, the signal was then smoothed using a three-point moving average filter. In order to obtain the periodic components from the hybrid motion artifact removal technique, which combines signal decomposition with adaptive filtering, some researchers also incorporated the singular value decomposition and the moving average filter. Both PPG recording and acceleration data (used as a reference) are fed into the adaptive filter in this manner.

A signal decomposition technique was used to eliminate any remaining motion artifact components from the original PPG signal following the use of an adaptive filter. PPG-based filtering methods can lessen the impact of noise, but they cannot provide consistently high accuracy. For example, when noise (e.g., in amplitude) crosses over the PPG peak. They may also require additional sensors, such as accelerometers or gyroscopes.

3.2.1.2. Envelope extraction and peak determination

This procedure generally encompasses extracting different features such as the peak and nadir, inclination of the signal, and signals 'envelope using universal and robust algorithms, for example, adaptive threshold and transform-based algorithms to find the signal peaks.

(1) Method of Adaptive Threshold

The adaptive threshold is a common technique for identifying PPG peaks. This technique uses a constant that is determined by the time intervals and frequency and temporal domain characteristics of the signals. Because the PPG wave shape is dynamic, the constant could be raised or decreased. As a result, several academics have suggested regenerating the threshold based on various characteristics, including the signal's standard deviation, preceding peaks, and sampling frequency. Numerous methods rely on adaptive thresholds. In certain studies, adaptive thresholding is fitted with a morphological filter to eliminate low sounds, and a slope sum function is employed to precisely locate the locations of peaks. Other people have also proposed an approach based on an adjustable threshold, which is followed by moving average and spline interpolation techniques in the event that the identified peaks exhibit clipping.

(2) Transform-Based Techniques

Moreover, PPG peak detection is specifically targeted with transformation-based techniques. The method's main approach is to extract the time domain and frequency domain features of the signal using a variety of linear transformations, such as wavelet transforms and Hilbert transformations.

The signal components and their corresponding peaks are extracted from the original signal through the use of different thresholds, such as crossing-zero or decision logic. The systolic peak was pinpointed by the experimenter in recent studies by combining the Hilbert transform with moving average and Shannon energy envelope techniques. A Hilbert duplex envelope method was suggested in other studies to detect PPG peaks. The upper and lower envelopes of the signal were obtained using the Hilbert transform. In the second stage, the peak of PPG is located by using the Hilbert transform to transform the upper and lower envelopes and retrieve the local maximum method at the end.

However, because it is challenging to precisely identify the systolic peak of the distorted PPG signal, existing transformation-based techniques remain inadequate for wearable device-based PPG. Even yet, the aforementioned technique for determining the PPG signal quality is precise and helpful. However, issues still exist, such as their sensitivity to environmental motion and noise, which leads them to differentiate between systolic peaks and false noise, which is another source of misleading readings. Generally speaking, it is still challenging to ensure the correctness of the

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experiment using existing methodologies if the patient is in a stable and unstable environment since it is simple for errors to emerge if there are many heart rates in the signal.

3.2.2. Frequency analysis

The application of frequency analysis represents a crucial technique for enhancing the precision of PPG signal interpretation. This is achieved by transforming the time-domain signals into frequency-domain signals, thereby facilitating an understanding of the fundamental attributes of heart rate and its fluctuations [1].

The Fast Fourier Transform (FFT) is an algorithm of great importance in the field of signal processing, whereby time-domain signals are converted into frequency-domain signals. By efficiently calculating the value of the Discrete Fourier Transform (DFT), it is possible to decompose complex time signals into sinusoidal and cosine components with varying frequencies, amplitudes and phases. The effectiveness of the FFT in heart rate monitoring has been demonstrated, particularly in conjunction with PPG technology. The FFT is used to analyse PPG signals, which reflect changes in blood volume due to cardiac activity. This typically encompasses the oscillatory component of the cardiac cycle. By transforming these signals into the frequency domain, the FFT is able to accurately identify the frequency of periodic fluctuations. Its ability to identify significant spectral peaks that correspond to the heart's natural beating frequency enables accurate heart rate measurements. DFT is defined as equation (1):

$$\boldsymbol{X}\left[\boldsymbol{k}\right] = \sum_{\boldsymbol{n}=0}^{\boldsymbol{N}-1} \boldsymbol{x}\left[\boldsymbol{n}\right] \cdot \boldsymbol{e}^{-\boldsymbol{j}(2\boldsymbol{\pi}/\boldsymbol{N})\boldsymbol{kn}} \tag{1}$$

Specifically, for a given time-domain signal represented by samples $\boldsymbol{x}[\boldsymbol{n}]$, where $[\boldsymbol{n}]$ is the index of each sample, the DFT $\boldsymbol{X}[\boldsymbol{k}]$ represents the frequency-domain component corresponding to the frequency index $\boldsymbol{k}$. This index ranges from 0 to $\boldsymbol{N}-1$ with $\boldsymbol{N}$ being the total number of samples. The transformation is achieved by multiplying each time-domain sample $\boldsymbol{x}[\boldsymbol{n}]$ by a series of complex exponentials, which serve as rotational factors, and then summing these products to produce each component $\boldsymbol{X}[\boldsymbol{k}]$ of the resulting frequency spectrum. This process reveals the frequency content of the signal. It can also enable further analysis and processing in the frequency domain.

The Discrete Fourier Transform (DFT) provides the theoretical framework necessary for transforming signals from the time domain to the frequency domain. However, its $\mathrm{O}(\mathrm{N}^2)$ computational complexity makes it inefficient for processing large-scale data. Consequently, the FFT was developed to reduce the complexity to $\mathrm{O}(\mathrm{N}\log\mathrm{N})$, significantly speeding up the process. The Cooley-Tukey algorithm is a prime example of an FFT approach. This method decomposes a DFT of length N into two smaller DFTs of length $\mathrm{N}/2$, each processing either the even or odd parts of the original sequence. This process recurs until the problem size is small enough to be solved directly. The results of these sub-problems are then combined using butterfly operations, culminating in the final DFT result [3]. The specific formula is equation (2):

$$\mathrm{X}\left[\mathrm{k}\right] = \mathrm{E}\left[\mathrm{k}\right] + \mathrm{e}^{-\mathrm{j}\frac{2\pi}{\mathrm{N}}\mathrm{k}}\mathrm{O}\left[\mathrm{k}\right] \tag{2}$$

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$E[k]$ and $O[k]$ represent the DFT results of the even and odd sequences, respectively. This systematic decomposition and restructuring facilitate the computational process, thereby rendering the FFT a valuable tool for rapid and efficient frequency domain analysis.

Following the application of the FFT for signal processing, prominent peaks corresponding to the heart rate are discerned within the frequency spectrum. Subsequently, this spectrum undergoes a comprehensive analysis to precisely locate these peaks and to distinguish the fundamental frequency related to cardiac rhythms from the secondary frequency components arising from other physiological activities. The computation of the heart rate is predicated on the frequencies of these primary peaks, which are then converted into BPM. This approach guarantees accurate monitoring and analysis of cardiac function.

The Short-Time Fourier Transform (STFT), which is based on the FFT, significantly enhances the analysis of heart rate variability within PPG signals. This method utilizes the FFT in short and consecutive time windows. It thereby effectively captures the dynamic changes of heart rate over time. STFT presents a dual portrayal of time and frequency and furnishes a sturdy solution for dissecting non-stationary signals, which are customary in cardiac monitoring. The STFT is able to track changes in frequency components by selecting the window function and appropriately adjusting the window size while maintaining temporal resolution. This allows rapid fluctuations in cardiac function to be detected and scrutinised [4]..

3.3. Machine learning

In the realm of heart rate monitoring, specifically within the application context of PPG technology, machine learning presents an exceedingly efficacious approach for the analysis and interpretation of heart rate data. Through the integration of advanced machine learning models like Random Forests, Support Vector Machines (SVM), and deep learning architectures such as Convolutional Neural Networks (CNN) and Long Short-Term Memory networks (LSTM), researchers are enabled to process extensive time-series data and automatically discern complex physiological patterns. These models outperform traditional signal processing methodologies on account of their capacity to self-adjust parameters in alignment with the data characteristics, thereby augmenting the precision of predictions and the caliber of decision support [5].

Before the implementation of machine learning models, the accurate preprocessing of PPG signals is of paramount importance for guaranteeing the quality of data input and maximizing the performance of the ultimate models. This preprocessing encompasses several essential steps. Firstly, noise reduction is carried out using filters to remove the interference caused by environmental factors or operational errors. Secondly, normalization is performed to bring all data to a uniform scale, thus alleviating the influence of dimensional differences. Thirdly, feature extraction is conducted to extract the most informative indicators from the raw signals. Upon the completion of these preprocessing steps, the data is prepared for training machine learning models, where the selection of the model and the training method is contingent upon the specific application context and the desired results.

In the training stage, a sufficient quantity of labelled data is required for the training and fine-tuning of the model parameters. In the validation phase, techniques such as cross-validation are employed to evaluate the generalisability and stability of the model. These procedures guarantee that the model retains robust performance when confronted with novel and unobserved data. These strategies are utilised to enhance the precision of heart rate monitoring and facilitate continuous assessment of health status in real-time scenarios.

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4. Challenges in PPG signal processing

4.1. Challenges and limitations in PPG signal processing

4.1.1. Motion artifacts

Motion artifacts are one of the biggest challenges in PPG signal processing. When a subject moves, the PPG sensor will be relatively displaced or suffer mechanical vibrations, which may introduce large-amplitude, low-frequency noise into the PPG signal. Such kinds of noise usually cause serious distortion of the real PPG waveform, and the required accurate physiological information, such as heart rate and blood oxygen saturation, cannot be precisely extracted.

Motion artifact characteristics vary with the type of motion. For instance, rapid limb movement can create spikes in the signal, and slow continuous movements can introduce baseline drift. These artifacts may turn out to be much larger in amplitude compared to the physiological PPG signal per se, especially in wearable PPG devices, where the sensor is much more exposed to influence by body movements.

4.1.2. Low Signal-to-Noise Ratio (SNR)

PPG signals are relatively weak, especially when blood perfusion in the measured tissue is low, or the sensor is of low sensitivity. There are various factors that could contribute to the poor signal-to-noise ratio of the PPG signal, such as light interference of ambient light, electrical noise generated by the sensor circuit, and biological noise generated by other physiological processes.

In such a case, ambient light may be the most critical noise contributor to PPG signals. A PPG sensor detects changes in the absorption and reflection of light by blood vessels, and the unwanted ambient light will also be detected by the sensor; hence, it adds unwanted noise to the signal. This particularly relates to outdoors or areas with a lot of light. The SNR of the PPG signal can also be reduced by electrical noise of the sensor circuitry, such as thermal noise and electromagnetic interference.

4.1.3. Individual variability

There is great individual diversity in the PPG signals. The characteristics of the PPG signal are affected by a number of factors, including age, gender, and skin pigmentation, as well as underlying health conditions. For example, in older adults, blood perfusion to the skin may be reduced, resulting in a weaker PPG signal. Light absorption and reflection in the PPG measurement could also be changed by skin pigmentation, resulting in variation of signal amplitude.

PPG signals may also be abnormal in people with certain medical conditions, including cardiovascular disease, diabetes, etc. The individual variability of PPG signals hampers the development of one-size-fits-all signal processing algorithms for PPG signals. One signal processing method works well for one person and not at all for another.

4.1.4. Complex physiological signals

PPG signals are never a pure reflection of changes in blood volume. It can be affected by many physiological processes simultaneously. For example, breathing modulates the PPG signal with small amplitudes and low frequencies. Furthermore, the autonomic nervous system also modifies the PPG signal via its effect on the diameter of blood vessels and blood flow.

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The physiological interactions that arise out of these simple physiological functions result in difficulty in isolating and accurately analyzing the PPG signal related to the desired physiological parameters, such as heart rate. This system has multiple overlapping signals, and hence the signal processing techniques must be complex enough for isolating and extracting the most relevant information.

4.2. Potential solutions

4.2.1. Adaptive filtering for motion artifacts

Motion artifacts can be reduced in the PPG signals by using the adaptive filtering techniques. These filters may change their parameters adaptively as a function of the input signal characteristics and of the noise. As an example, a least-mean-squares (LMS) [6] adaptive filter can be used to estimate and remove the motion induced noise from the PPG signal.

The major advantage of adaptive filtering will then be the tracking of changes that may occur in noise characteristics in general. Since the pattern of motion of the subject changes with time, this filter will adapt itself for the continuous removal of motion artifacts. Moreover, their advanced forms may also include additional information, such as accelerometer data from a wearable device, toward the detection and removal of accurate noise related to motion.

4.2.2. Signal enhancement for low SNR

A number of signal enhancement techniques can be employed to improve the SNR of PPG signals [7]. An optical filter could be used to reduce ambient light interference. Such a filter would ideally allow only the wavelength of light that is involved in the PPG measurement and screen out all other wavelengths.

Another technique is to use signal averaging. Large numbers of PPG signal samples are averaged over a certain period to reduce random noise within the signal. However, such methods may be unsuitable for real-time applications since response needs to be quick. In such applications, advanced signal processing algorithms such as wavelet-based denoising may be employed. Wavelet-based filtering will remove the noise without removing the important features of the PPG signal.

4.2.3. Personalized signal processing for individual variability

For the issue of individual variability, personalized algorithms can be developed to handle it in signal processing. It can involve collecting a large amount of PPG data from lots of different people with different characteristics and, with machine learning techniques, generating individualized models.

For example, training a neural network on a person-specific dataset in order to acquire features about his/her PPG signal. Further, this personalized model can be used for subsequent, accurate processing of their PPG signals. There is also a chance that some wearables PPG could make them adaptively change their parameters of signal processing, depending either on the user's initial calibration data or on over-time usage patterns.

4.2.4. Advanced signal decomposition for complex signals

Advanced methods for signal decomposition can be carried out to deal with the complex physiological signals of PPG. Included here is the so-called empirical mode decomposition (EMD).

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In this way, a complex PPG signal can be decomposed, using EMD, into a set of intrinsic mode functions (IMFs), each of them characterizing a particular frequency component of the signal [8].

By analyzing these IMFs, the relevant physiological components, such as the heart rate-related component, can be isolated and further analyzed. Another approach is to use principal component analysis (PCA) to reduce the dimensionality of the PPG signal while retaining the most important information [9]. PCA can help separate overlapping physiological signals and improve the accuracy of parameter extraction.

5. Future prospects

5.1. Advancing signal processing in PPG

Photoplethysmography (PPG) has become an essential technology in healthcare, especially for devices that monitor heart health without invasive procedures. As wearable devices become popular and clinical systems adopt more advanced methods, improving how we process PPG signals has become increasingly important. Researchers recently focused on four key areas to make these devices more accurate and reliable:

Better Noise Reduction Methods

PPG signals often suffer from interference, such as sudden movements, changes in lighting, or natural variations in the human body. To address these issues, new filtering techniques and advanced computational approaches are being used. For instance, some researchers have found success with deep learning methods specifically designed to remove unwanted noise, producing cleaner and more trustworthy data.

Combining Multiple Sensor Data

To enhance accuracy, researchers have started pairing PPG with other types of sensors, like accelerometers or ECG devices, allowing a more complete understanding of health. By using advanced methods such as Kalman filters or convolutional neural networks, these systems effectively cross-check and combine data from various sources. This not only helps minimize motion-related errors but also provides deeper insights into overall cardiovascular health.

Efficient Processing on Small Devices

Since wearable devices typically have limited battery life and computational resources, efficient and lightweight signal processing is crucial. Techniques like sparse data representation or "edge computing" (processing data directly on wearable devices, rather than sending it elsewhere) allow real-time monitoring while extending battery life. These optimizations help ensure devices can run continuously without sacrificing accuracy.

Health Prediction and Analysis

Today's PPG technology increasingly includes predictive analytics, using methods like gated recurrent units and attention-based algorithms to catch small changes in heart patterns that might indicate early stages of heart conditions. Additionally, tracking long-term trends helps personalize health care, enabling the detection of subtle changes compared to an individual's normal health patterns, providing early warnings before serious issues develop.

All these advancements make PPG technology more useful and reliable for healthcare applications, leading to smarter, personalized wearable devices. Looking forward, further research might aim for even smaller and lighter devices, easier connection between different health monitoring systems, and more precise predictive capabilities through continued innovation in processing algorithms.

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5.2. Future directions for PPG technology

Recent improvements in photoplethysmography (PPG) signal processing have expanded its use into new areas of healthcare and personal identification. As this technology evolves, several exciting opportunities have opened up, offering more than just basic heart monitoring:

Detailed Health Tracking

PPG is starting to measure more than just pulse rate. By carefully analyzing small changes in blood flow, newer devices might soon monitor breathing patterns, track how our nervous system reacts to different situations, and even detect signs of changes in metabolism. Capturing these additional health signs could make it easier to spot early warning signs of health conditions like diabetes or blood circulation problems before they become serious.

Improved Access to Healthcare

With advanced PPG sensors being built into wearable devices, people might soon receive medical-grade checkups at home. Better signal analysis means doctors could reliably monitor patients remotely, helping to bridge gaps in healthcare access. This is especially important for those who live far from hospitals or who need frequent follow-up care, such as people with chronic diseases or those recovering from surgery.

Secure Identification Methods

Interestingly, everyone's blood flow has unique patterns. By analyzing these personal characteristics hidden within PPG signals, it might be possible to create new ways of securely identifying individuals. Such methods could offer easier and more secure alternatives to traditional passwords or fingerprint scans for unlocking phones, computers, or other personal devices.

Monitoring Emotional and Mental States

PPG measurements, especially something called heart rate variability, can indicate emotional and mental health. By continuously watching these subtle signals, devices could detect when someone is stressed or anxious, providing opportunities to intervene early. This could be especially helpful for people managing mental health challenges or those needing support during stressful periods.

Customized Fitness Recommendations

Athletes and fitness enthusiasts could greatly benefit from advanced PPG devices that analyze how their hearts and circulation respond during exercise. Future wearables might offer personalized workout suggestions based on real-time cardiovascular responses. These insights could help individuals optimize their training routines, recovery times, and reduce the risk of injuries by adapting workouts specifically to their body's needs.

Overall, these advances show how PPG technology is shifting from basic heart-rate tracking toward a comprehensive health-monitoring tool. Future research could focus on making signals clearer, creating standard ways of interpreting data, and testing how well these innovations work across different groups of people. By pairing improved sensor technology with advanced analysis techniques, PPG could play an increasingly important role in personalized healthcare and beyond.

6. Conclusion

In conclusion, accurately processing PPG signals remains an important but challenging task, especially as wearable health devices become more common in daily life. Although problems like interference from body movements and noisy environments still exist, there’s continuous progress in finding better solutions. Methods to handle these issues range widely, from basic filtering techniques to more recent approaches involving machine learning, each with its own strengths and weaknesses. Understanding these differences helps users choose the right solution based on their particular needs

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and situations. Looking forward, combining data from multiple types of sensors, creating personalized analysis techniques, and making real-time monitoring easier could further expand how we use PPG technology. As researchers keep improving these areas, PPG will likely play a bigger role not just in hospitals and clinics, but also in personal health tracking—giving people more convenient, non-invasive ways to monitor their health in everyday life.

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References

[1] Cho, J.M. et al. (2012) 'A preliminary study on photoplethysmogram (PPG) signal analysis for reduction of motion artifact in frequency domain', 2012 IEEE-EMBS Conference on Biomedical Engineering and Sciences, 2, pp. 28–33. doi: 10.1109/iecbes.2012.6498141.

[2] Aisuwarya, R., Hendrick, H. and Meitiza, M. (2019) 'Analysis of cardiac frequency on photoplethysmograph (PPG) synthesis for detecting heart rate using Fast Fourier transform (FFT)', 2019 International Conference on Electrical Engineering and Computer Science (ICECOS), 67, pp. 391–395. doi: 10.1109/icecos47637.2019.8984512.

[3] Shirbhate, R., Panse, T. and Ralekar, C. (2015) 'Design of parallel FFT architecture using Cooley Tukey algorithm', 2015 International Conference on Communications and Signal Processing (ICCSP), 56, pp. 0574–0578. doi: 10.1109/iccsp.2015.7322551.

[4] Jong, G.-J., Aripriharta and Horng, G.-J. (2017) 'The PPG physiological signal for heart rate variability analysis', Wireless Personal Communications, 97(4), pp. 5229–5276. doi: 10.1007/s11277-017-4777-z.

[5] Oyeleye, M. et al. (2022) 'A predictive analysis of heart rates using machine learning techniques', International Journal of Environmental Research and Public Health, 19(4), p. 2417. doi: 10.3390/ijerph19042417.

[6] L. Zhang, X. Yu, H. Xie, J. Lin, and Z. Wang, "Removal of Motion Artifacts in PPG Signals Based on the CEEMDAN-MPE and VS_LMS Adaptive Filter, " in IEEE Transactions on Instrumentation and Measurement, vol. 73, pp. 1-10, 2024, Art no. 4010610, doi: 10.1109/TIM.2024.3453341.

[7] Kazemi K, Laitala J, Azimi I, Liljeberg P, Rahmani AM. Robust PPG Peak Detection Using Dilated Convolutional Neural Networks. Sensors. 2022; 22(16): 6054. https: //doi.org/10.3390/s22166054

[8] Changying Gu and Qi Wang, "Laser self-mixing interference displacement signal filtering method based on empirical mode decomposition and wavelet threshold, " 2024 Meas. Sci. Technol. 35 045201, doi 10.1088/1361-6501/ad166c

[9] M. A. Motin, C. K. Karmakar, and M. Palaniswami, "Integrated Empirical Mode Decomposition with Principal Component Analysis: A New Method for Extracting Respiratory Frequency and Heart Rate from Photoelectromechanical Pulse Wave Signals, " IEEE Journal of Biomedical and Health Informatics, Volume 22, Issue 3, Pages 766-774, May 2018, doi:10.1109/JBHI.2017.2679108.