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ANALYSIS OF METHODS AND ALGORITHMS FOR REMOTE PHOTOPLETHYSMOGRAPHY SIGNAL DIAGNOSTIC AND FILTERING

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Abstract: Remote photoplethysmography is becoming increasingly common in telemedicine for non-invasive physiological monitoring of the cardiovascular system. However, signal reliability has been reduced due to noise and artifacts, which requires reliable diagnostic and filtering methods. The research aim is to evaluate existing methods and algorithms for diagnosing and filtering remote photoplethysmography signals to improve the accuracy of human cardiovascular monitoring. A systematic review has identified methodologies for improving remote photoplethysmography signals by analyzing their principles, implementation, and effectiveness. Various approaches have been analyzed, including the use of statistical computing, adaptive filters, and machine learning algorithms. Each approach offers unique advantages and limitations in terms of noise reduction and artifact removal.

***Index Terms*: filtering; photoplethysmography; heart rate variability; wavelet transform**

I. INTRODUCTION

Remote photoplethysmography (RPPG) has transformed the field of physiological monitoring by providing a non-invasive means to assess vital signs using camera-equipped devices remotely. As telemedicine and remote healthcare continue to grow, the analysis of RPPG signals is essential in enabling correct and reliable health assessments outside of traditional clinical practice settings. Exploring and evaluating methods and tools for analyzing RPPG signals are crucial endeavors in contemporary biomedical research.

Accurately interpreting RPPG signals has significant implications for personalized healthcare delivery, disease management, and wellness monitoring in the current era of rapid technological advancements and increasing reliance on telehealth solutions. Furthermore, the scalability and accessibility provided by RPPG make it particularly relevant in contexts where traditional healthcare infrastructure may be limited or inaccessible.

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II. LITERATURE REVIEW AND PROBLEM STATEMENT

RPPG has become increasingly important for non-invasive physiological monitoring. Numerous methods and algorithms have been developed to refine the remote diagnosis and filtering of PPG signals. These approaches include noise reduction, motion artifact mitigation, and signal enhancement [1], often using machine-learning algorithms for automated event detection [2]. Integration into wearables and telemedicine underscores the importance of robust signal processing for reliable remote PPG diagnosis.

Despite advances, challenges remain in achieving accurate RPPG signal diagnosis and filtering [3]. Issues such as motion artifacts and ambient light interference affect signal quality. Effective signal processing tailored for remote PPG is critical and requires advanced algorithms for noise reduction, artifact removal, and signal enhancement. There's also a need for automated event detection, which involves the integration of machine-learning techniques. This research aims to analyze existing methods, identify shortcomings, and propose novel approaches for improved RPPG-based health monitoring.

III. SCOPE OF WORK AND OBJECTIVES

The main idea of algorithms developed for analyzing RPPG is to use optical imaging to detect minor changes in skin color caused by pulsating blood flow. These algorithms are aimed at extracting physiological parameters, such as the Blood Volume Pulse (BVP) and Pulse Rate (PR), using advanced computational methods. The aim is to provide a comprehensive analysis of the methods and tools used to study RPPG signals, which will make a significant contribution to the ongoing discourse on remote health monitoring by clearly clarifying the principles underlying different analytical approaches and allowing a confident assessment of their effectiveness in extracting important physiological information about the cardiovascular system.

IV. REMOTE PHOTOPLETHYSMOGRAPHY SIGNAL

Facial detection techniques are commonly used in these algorithms, followed by the identification of regions of interest (ROI) within captured images. Architecture design [1] in Fig. 1 describes subsequent processing that involves selectively filtering skin pixels based on empirically derived color thresholds, which helps to isolate signals indicative of blood perfusion dynamics. Advanced signal processing techniques, such as clustering algorithms and bandpass filtering, effectively mitigate the effects of interfering factors, such as motion artifacts and environmental noise [2]. These algorithmic approaches ease non-invasive and continuous monitoring of cardiovascular parameters, with promising implications for various fields, including healthcare, health monitoring, and human-computer interaction research.

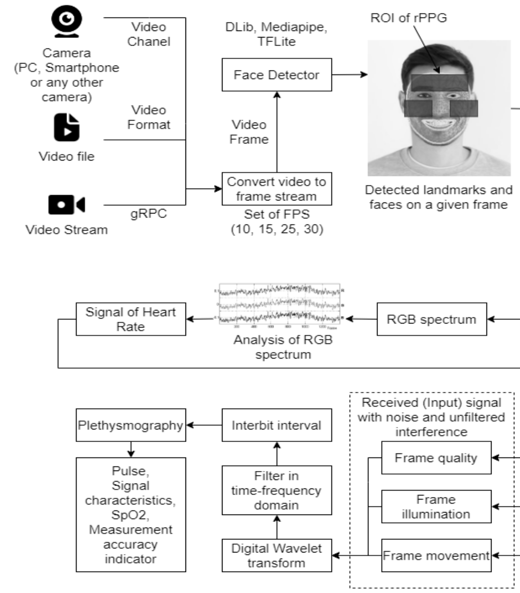

Fig. 1. Architecture design of simple remote photoplethysmographic system

The RPPG principle used for the measurement of Blood Volume Pulse (BVP) is based on differential light absorption characteristics of blood [3] in comparison to surrounding tissues. It can be demonstrated that the passage of blood through blood vessels results in significant absorption of light and reduced reflection, which leads to periodic alterations in skin color. RPPG constitutes a measurement method using these skin color changes to gauge BVP levels. The procedural steps for RPPG acquisition involve the first detection of a facial structure within an image frame utilizing the Viola-Jones algorithm, followed by extraction of a facial region-of-interest (ROI) employing a kernelized correlation filter.

V. FILTERING OF REMOTE PHOTOPLETHYSMOGRAPHY SIGNAL

In the field of remote photoplethysmography (RPPG) analysis, various filtering techniques are utilized to enhance the extraction and characterization of physiological signals from optical data. These filters encompass both conventional signal processing methods and sophisticated computational approaches, each tailored to tackle specific challenges encountered in the analysis of remote photoplethysmographic signals. Bandpass filtering is a technique commonly used in RPPG analysis. It is designed to attenuate frequency components outside a specified range while preserving signal components of interest. This technique is particularly useful in isolating the pulsatile characteristics inherent in photoplethysmographic signals, effectively suppressing noise and motion artifacts that may obscure physiological information [4].

The Fast Fourier Transform (FFT) is a widely used tool for analyzing RPPG signals in the frequency domain. By decomposing time-domain signals into their constituent frequency components, researchers can find dominant frequency peaks that correspond to cardiovascular dynamics. This enables the quantitative assessment of pulse rate and spectral characteristics of photoplethysmographic signals. Advanced signal decomposition techniques, such as Independent Component Analysis (ICA) and Principal Component Analysis (PCA), can be useful tools for extracting relevant signal components from multi-channel photoplethysmographic data.

Savitzky-Golay filtering is a highly effective polynomial smoothing technique that is commonly used in RPPG analysis. It is particularly suitable for enhancing the signal-to-noise ratio in photoplethysmographic recordings. This technique fits local polynomial regressions to the signal, effectively suppressing noise without introducing significant distortion.

Recent advances in machine learning, specifically deep learning methods, have shown great promise in RPPG analysis tasks. Deep learning models trained on large photoplethysmographic signal datasets can automatically extract complex features and patterns, significantly enhancing pulse rate estimation accuracy and physiological signal characterization.

Kalman filtering is a powerful and adaptive recursive estimation technique that is ideal for real-time applications. It adjusts filter parameters based on dynamic models of physiological processes and measurement noise, making it perfect for denoising signals and estimating parameters in RPPG analysis.

Wavelet-based denoising techniques effectively suppress noise and artifacts in RPPG signals while preserving signal features across different time scales. The signal is decomposed into wavelet coefficients, and noise components are selectively removed at multiple resolutions, resulting in significantly enhanced signal quality in photoplethysmographic recordings.

In summary, it is crucial to use a variety of filtering techniques, from traditional signal processing to advanced machine learning algorithms, for analyzing remote photoplethysmographic signals. These approaches allow researchers to effectively extract, denoise, and characterize physiological signals.

A. BANDPASS FILTERING

Bandpass filtering is a fundamental signal processing method that is extensively used in the examination of remote photoplethysmography (RPPG) signals. One of the key benefits of bandpass filtering is its capacity to selectively isolate specific frequency components within a specified range while simultaneously attenuating signals outside this range. The extraction of important physiological information from photoplethysmographic signals, such as the Blood Volume Pulse (BVP) and Pulse Rate (PR), can be quantitatively assessed through this characteristic.

Bandpass filtering is an effective tool for reducing the impact of noise and artifacts in RPPG recordings, particularly those caused by fluctuations in ambient light and motion. Bandpass filters enhance the accuracy and reliability of parameter estimation and signal interpretation by suppressing high-frequency noise components while retaining pulsatile signal characteristics. This capability is crucial for ensuring the fidelity of physiological signal representation, particularly in real-world scenarios where environmental disturbances are prevalent.

However, with proper attention to these parameters, bandpass filtering can be a highly effective tool for analyzing physiological signals. Bandpass filtering has limitations, such as the need for precise specification of filter parameters, including the lower and upper cutoff frequencies, to effectively capture the desired signal components. Improper selection of these parameters may lead to inadvertent attenuation of relevant physiological signals or retention of unwanted noise, potentially distorting the interpretation of RPPG data. Bandpass filters may present challenges in adapting to dynamic changes in signal characteristics or environmental conditions due to their static nature.

Bandpass filtering has the potential to introduce artifacts or distortions to the signal. This is especially true if the filter parameters are not properly adjusted or if the signal contains non-stationary components. These distortions can compromise the accuracy and reliability of signal analysis, requiring additional post-processing steps to mitigate their effects. Bandpass filtering provides significant benefits in isolating relevant frequency components and suppressing noise in RPPG signals. It is important to consider the limitations of bandpass filtering to ensure accurate signal interpretation and meaningful physiological insights.

B. FAST FOURIER TRANSFORM FILTERING

Using Fast Fourier Transform (FFT) filtering is a fundamental signal processing technique that plays a crucial role in the analysis of remote photoplethysmography (RPPG) signals. Its efficacy in decomposing time-domain RPPG signals into their constituent frequency components is a prominent advantage that makes it a valuable tool in this context. The FFT efficiently analyzes the frequency content of photoplethysmographic signals, allowing for the quantitative assessment of physiological parameters such as the Blood Volume Pulse (BVP) and Pulse Rate (PR). Furthermore, FFT filtering enables frequency domain analysis of RPPG signals, providing insights into the spectral characteristics and frequency distribution of cardiovascular dynamics. This capability identifies dominant frequency peaks associated with pulsatile blood flow, facilitating the detection of subtle changes in cardiovascular function and providing valuable information for clinical diagnosis and monitoring. FFT filtering is a versatile tool for spectral analysis, allowing researchers to explore relationships between different frequency components and their correlation with physiological phenomena. However, its susceptibility to spectral leakage, particularly in cases where the signal duration is limited or non-stationary components are present, is a notable drawback. This can distort frequency domain representations of RPPG signals, leading to inaccuracies in parameter estimation and signal interpretation [5].

Accurate interpretation of FFT results requires careful consideration of windowing and resolution parameters. Improper selection of these parameters can negatively impact the accuracy and reliability of spectral analysis. FFT filtering may also introduce artifacts or amplify noise, particularly in cases where the signal-to-noise ratio is low or when preprocessing steps are inadequate in mitigating noise sources. Researchers must use FFT filtering judiciously to ensure accurate and meaningful signal analysis, despite its valuable insights into the frequency domain characteristics of RPPG signals.

C. ICA AND PCA FILTERS

Independent Component Analysis (ICA) and Principal Component Analysis (PCA) filtering are essential signal processing techniques extensively used in the analysis of remote photoplethysmography (RPPG) signals. Both techniques have distinct advantages and disadvantages that are relevant to their utilization in this domain. However, when used appropriately, these techniques can significantly enhance the quality and accuracy of RPPG signal analysis. ICA and PCA filtering have the advantage of decomposing multi-channel RPPG data into statistically independent or orthogonal components, respectively. This allows for the extraction of relevant physiological signals from complex and noisy recordings.

ICA filtering is particularly effective in separating sources contributing to RPPG signals, such as hemodynamic changes and motion artifacts, by exploiting statistical independence assumptions [6]. ICA filtering and PCA filtering are powerful techniques that enhance the robustness and accuracy of signal extraction. ICA filtering isolates independent components associated with cardiovascular dynamics, making it particularly useful in the presence of confounding factors or overlapping sources. Similarly, PCA filtering leverages orthogonal transformations to identify dominant patterns of variation within RPPG data, enabling researchers to isolate signal components representing physiological phenomena while suppressing noise and artifacts.

ICA and PCA filtering obtain valuable insight into the underlying structure of RPPG signals, enabling dimensionality reduction and feature extraction in subsequent analysis. These techniques are essential for identifying important features and patterns within RPPG data, ultimately improving the interpretability and discriminability of extracted signals. ICA and PCA filtering support exploratory analysis of RPPG recordings, enabling researchers to uncover relationships between different signal components and their correlation with physiological parameters.

ICA and PCA filtering can be useful, but they have limitations. Their assumption of statistical independence or orthogonality may not hold true for all signal sources present in RPPG recordings, which can lead to inaccuracies in signal separation and the extraction of spurious components or artifacts. ICA and PCA filtering may reduce sensitivity to subtle variations in RPPG signals, particularly when signal components are highly correlated or non-stationary. It is important to carefully consider the underlying assumptions and limitations of these techniques when interpreting ICA and PCA results. Proper selection of parameters and model specifications is crucial for ensuring the accuracy and reliability of signal decomposition. Incorrect choices can lead to misinterpretations of RPPG data and incorrect conclusions. Additionally, the implementation of ICA and PCA filtering can be computationally complex and resource-intensive, particularly for large-scale or high-dimensional datasets.

In conclusion, researchers should consider the advantages and limitations of ICA and PCA filtering for signal decomposition and feature extraction in RPPG analysis. These techniques can be effectively leveraged for meaningful signal interpretation and physiological insights [6].

D. SAVITZKY-GOLAY FILTERING

Savitzky-Golay filtering stands as a fundamental signal processing technique extensively used in the analysis of remote photoplethysmography (RPPG) signals, presenting distinct advantages and disadvantages pertinent to its application in this domain. Savitzky-Golay filtering effectively mitigates high-frequency noise and artifacts present in RPPG recordings while preserving the underlying signal characteristics. Local polynomial regressions can effectively reduce noise without distorting the signal, making Savitzky-Golay filters ideal for improving the signal-to-noise ratio in photoplethysmographic data [7].

Furthermore, Savitzky-Golay filtering is computationally efficient, enabling real-time or near real-time processing of large datasets in RPPG analysis. Savitzky-Golay filters are the preferred choice in RPPG research and applications due to their simplicity, computational efficiency, and robustness to variations in signal characteristics. They consistently outperform other filtering techniques across different datasets and experimental conditions and require less sensitivity to parameter selection.

Savitzky-Golay filtering, while useful, has limitations. Its finite impulse response nature can cause signal distortion or phase shift, particularly when the filter order is high, or the signal contains transient components. It is important to note that Savitzky-Golay filters may have limited adaptability to non-stationary or rapidly changing signal characteristics. This can compromise their efficacy in capturing dynamic physiological phenomena. It is worth considering alternative filtering methods that may be better suited to these types of signals. Proper selection of filter parameters, such as window size and polynomial order, is crucial for achieving effective Savitzky-Golay filtering. Incorrect parameter selection can lead to inaccurate and unreliable RPPG analysis results due to over-smoothing or under-smoothing of the signal. Savitzky-Golay filtering may not eliminate all sources of noise and artifacts in RPPG recordings. To attain the highest possible signal quality, it is necessary to utilize supplementary preprocessing steps or alternative filtering techniques.

In conclusion, Savitzky-Golay filtering significantly improves noise suppression and signal smoothing in RPPG analysis [7]. Its limitations must be carefully considered and parameterized appropriately to ensure accurate and meaningful signal interpretation. By leveraging the strengths of Savitzky-Golay filtering while addressing its shortcomings, researchers can enhance the robustness and reliability of RPPG analysis results for various clinical and research applications.

E. WAVELET FILTERING

Wavelet filtering is a powerful signal processing technique that is widely used in the analysis of remote photoplethysmography (RPPG) signals. It offers distinct advantages and disadvantages when applied in this domain. One of its most significant advantages is its ability to effectively suppress noise and artifacts while preserving signal features across different time scales. Decomposing RPPG signals into wavelet coefficients at multiple resolutions allows for selective noise removal, improving the signal-to-noise ratio and the accuracy of parameter estimation and signal interpretation.

Wavelet filtering is a versatile and adaptable method for denoising signals in RPPG analysis. Researchers can customize the filtering process to the unique characteristics of the signal and noise sources present in the data. Wavelet filters can be tailored to target specific frequency bands or spatial regions within the signal, resulting in precise noise suppression while minimizing distortion of the underlying physiological information. Wavelet filtering is a powerful tool for detecting and removing transient or non-stationary noise components in RPPG recordings affected by motion artifacts or environmental disturbances [8].

It is important to note that, like any method, it has its limitations. The complexity involved in selecting parameters and designing filters, especially when the signal has multiple overlapping components or non-linearities, can be overcome with confidence and ability in the field. To achieve the best denoising performance and avoid artifacts or signal distortion, it is essential to select the appropriate wavelet type, decomposition level, and thresholding method. Wavelet filtering can introduce edge effects or ringing artifacts at the boundaries of the signal, potentially affecting the accuracy and reliability of the results.

Wavelet filtering can present challenges in real-time or near real-time applications, especially when dealing with large datasets or high-resolution signals. However, with proper optimization, wavelet decomposition and reconstruction can be made scalable and applicable in resource-limited environments or embedded systems [8]. While wavelet filtering offers significant advantages in noise suppression and signal denoising in RPPG analysis, it may be difficult to interpret for non-experts due to the complexity of wavelet transforms and thresholding techniques. However, it is important to note that these limitations can be overcome with proper optimization. Overall, wavelet filtering is a powerful tool for RPPG analysis when used correctly.

To ensure accurate and meaningful signal interpretation, researchers must carefully consider the limitations of wavelet filtering and optimize its parameters. To improve the robustness and reliability of RPPG analysis results for various clinical and research applications, researchers can confidently leverage the strengths of wavelet filtering while addressing its shortcomings.

F. KALMAN FILTERING

Kalman filtering is a crucial signal processing technique in remote photoplethysmography (RPPG) analysis, offering a multitude of advantages. One key advantage is its adaptive nature, which enables real-time estimation and tracking of parameters such as the Blood Volume Pulse (BVP) and Pulse Rate (PR). Kalman filters enhance accuracy and reliability by iteratively adjusting filter parameters based on dynamic models and noise, making it a highly effective tool for RPPG analysis. The integration of multimodal sensor data and personalized physiological models improves signal quality. Kalman filtering, despite its computational complexity in high-dimensional or non-linear systems, enhances RPPG signal analysis and offers valuable insights for various applications when properly applied and optimized [4].

In conclusion, Kalman filtering significantly enhances adaptive signal processing and parameter estimation in RPPG analysis. Researchers must carefully consider the limitations and challenges of this technique to effectively leverage it for meaningful signal interpretation and physiological insights. To enhance the robustness and reliability of RPPG analysis results for various clinical and research applications, we must address the computational complexity and interpretability issues associated with Kalman filtering.

G. DEEP LEARNING

Deep learning is a powerful signal processing technique in remote photoplethysmography (RPPG) analysis, with distinct advantages. One major advantage is its ability to automatically extract complex features from RPPG data without explicit feature engineering. Deep learning models, such as CNNs and RNNs, learn hierarchical representations, which significantly enhance accuracy and robustness. Deep learning incorporates multi-modal data sources to enhance parameter estimation and identify subtle physiological changes. Although large, labeled datasets are required for training, their effectiveness is unparalleled. While deep learning models may lack interpretability, their computational complexity can be managed in resource-constrained environments [9]. Deep learning significantly improves RPPG signal analysis when its challenges are carefully considered.

While deep learning offers significant advantages for automatic feature extraction and multimodal data integration in RPPG analysis, researchers must carefully consider its limitations and challenges. To enhance the accuracy, robustness, and clinical utility of RPPG signal analysis for various applications, researchers must address issues related to data availability, interpretability, and computational complexity [9]. The language should be formal and free from grammatical errors, spelling mistakes, and punctuation errors. It is important to avoid subjective evaluations and maintain a clear, concise tone [10].

Main tasks of the paper are the following: assess the current state-of-the-art methods and algorithms used in performing RPPG signal that is processing for diagnostic purposes; review literature, patents, and existing software to identify the strengths and limitations of different approaches; compare the performance of different algorithms in terms of accuracy, reliability, computational efficiency, and robustness to noise and motion artifacts. The objective of this research is to investigate techniques to optimize RPPG signal processing algorithms for remote monitoring applications. This includes considerations such as real-time processing, energy efficiency for battery-powered devices, and adaptation to varying environmental conditions. The usability and practicality of the developed algorithms must be assessed about their integration into remote monitoring systems. Research objectives focus on advance the field of remote photoplethysmography signal analysis by developing robust algorithms that can improve the accuracy and reliability of diagnostic information obtained from remote sensors (cameras), thereby facilitating early detection and monitoring of various health conditions. The main goal is to determine the best adaptive method for analyzing RPPG signals, considering the accuracy and limitations of each method. An error of more than 5 bpm is considered unacceptable for analyzing RPPG signals, so the selected method should have the smallest error.

VI. FILTERS EVALUATION

Filters are crucial for evaluating signal processing methods for remote photoplethysmography (RPPG) analysis. A bandpass filter isolates certain frequency components, while an FFT provides frequency domain analysis. ICA and PCA decompose multichannel data to improve signal extraction. Savitzky-Golay filters effectively suppress noise, and deep learning models provide automatic feature extraction. Kalman filters provide adaptive processing, and wavelet filtering offers versatile noise reduction and feature extraction [4].

Main stages that filters must perform:

- Noise suppression (Filters must effectively suppress the noise inherent in RPPG signals).
- Feature extraction (filters should allow for the extraction of relevant physiological features from RPPG signals, enabling the identification and analysis of pulsatile cardiovascular dynamics).
- Adaptability (filters should demonstrate adaptability to varying signal characteristics, including transient changes and non-stationary components inherent to physiological processes).
- Interpretability (filters should provide interpretable results, allowing researchers and clinicians to understand the extracted features and their implications for physiological assessment.
- Computational efficiency (filters must be computationally efficient to ensure timely processing of RPPG signals, particularly in real-time applications or resource-constrained environments).

The main criterion for evaluating the comparison of algorithms is the value of the root mean square (1) to compare the efficiency and accuracy of different approaches using a single set of video datasets with the following equation:

$$RMSE = \sqrt{\sum (y_i - \hat{y}_i)^2 / (N - P)} . \quad (1)$$

y is the actual value for the observation; ŷ is the predicted value for the observation; N is the number of observations; P is the number of parameter estimates (constant).

The root mean square error (RMSE) is calculated by first determining the residual for each observation data and then squaring it. The sum of all squared residuals is then calculated and divided by the error degrees of freedom in the model (difference between the number of observations and parameter estimates) to find the average squared residual, which is more technically known as the mean squared error (MSE). Finally, the square root is taken to find the RMSE.

RMSE is a key metric in research, as it enables the quantification of the accuracy of predictions, facilitates the evaluation and comparison of models, guides decision-making processes, and provides a standardized measure for error analysis. In general, RMSE is the square root of the average of squared differences between predicted and observed values.

Ultimately, the choice of RPPG filter depends on the specific application requirements, balancing factors like noise robustness, computational efficiency, and adaptability to motion artifacts. Considering all the critical characteristics and features of the methods under consideration, a comparative table (see Table 1) was created to show the main advantages and disadvantages of each method.

Table 1

Comparison of RPPG filters

Filter Name	Advantages	Disadvantages
Bandpass Filter	Effective noise suppression	Critical parameter selection
FFT	Enables spectral analysis	May miss transient components
ICA	Enhances signal extraction	Requires large, labeled datasets
PCA	Improves signal analysis	May miss subtle variations
Savitzky-Golay	Enhances signal-to-noise ratio	Computational complexity
Deep Learning	Automatic feature extraction	Requires large training datasets
Kalman Filters	Real-time estimation and tracking	Computational complexity
Wavelets	Preserves signal features	High computational complexity

Filters perform a critical role in the analysis of remote photoplethysmography (RPPG) signals, contributing to noise reduction, feature extraction, and parameter estimation. This evaluation is aimed at scrutinizing various filters commonly used in RPPG analysis, delineating their main steps, and assessing their effectiveness in addressing key requirements inherent in the analysis process (see Table 2).

The evaluation includes consideration of noise suppression, signal extraction, adaptability, computational efficiency, and interpretability, which are critical to selecting appropriate filters in RPPG analysis. Each filter has its advantages and limitations, which emphasizes the importance of tailoring the selection to the specific needs of RPPG data analysis.

Table 2

Metrics for RPPG filters

Filter Name	Processing	Performance
Bandpass Filter	Manual	RMSE: 6.11 bpm
FFT	Manual	RMSE: 4.63 bpm
ICA	Automated face tracker	RMSE: 1.24 bpm
PCA	Automated face tracker	RMSE: 1.43 bpm
Savitzky-Golay	Manual	RMSE: 1.24 bpm
Deep Learning	Manual	RMSE: 1.51 bpm
Kalman Filters	Automated face tracker faces	RMSE: 2.16 bpm
Wavelets	Manual	RMSE: 1.19 bpm

The analysis, which is commonly used for RPPG, showed that the root mean square error (1) for different types of filters indicates the effectiveness of these filters for noise reduction, feature extraction, and parameter estimation (RMSE is about 1 bpm). The low RMSE values (Wavelet, Savitzky-Golay, Deep Learning) across different filters indicate accurate signal processing, showcasing their potential for enhancing the accuracy and reliability of RPPG analysis in diverse applications. Evaluating the RMSE comprehensively provides valuable insights into the performance metrics of each filter. This allows researchers and clinicians to confidently select appropriate filters tailored to specific research or clinical requirements. Further advancements in filtering techniques are imperative for addressing the evolving challenges in RPPG analysis and optimizing the accuracy of physiological parameter estimation. Overall, the RMSE analysis underscores the importance of robust signal processing techniques in RPPG analysis.

When comparing the different methods (Table 2), it should be noted that Bandpass Filter and FFT have too large errors (from 3 bpm to 5 bpm) in calculating the heart rate, especially in videos with motion in the frame or variable lighting. Kalman Filter performs poorly with signals that have little information, such as low camera resolution. ICA, PCA, Savitzky-Golay, and Deep Learning have good accuracy rates (about 1.5 bpm), but when changes are made to the characteristics of the video stream or external factors, they lose their effectiveness (from 2 to 4 bpm) until the settings are adjusted. The regular performance of wavelet transform is 1.19 bpm based on analyzed examples. Wavelet transform is also sensitive to external factors, but with the right choice of parent wavelet functions, the efficiency will remain within 1.5 bpm.

VII. CONCLUSION

In the evaluation of filters for analyzing remote photoplethysmography (RPPG) signals, each technique presented distinct advantages and limitations. Among the array of filters assessed, the wavelet filter emerged as a particularly promising solution for RPPG analysis. Wavelet filtering offered a versatile approach to noise suppression and feature extraction, effectively removing noise while preserving signal features across different time scales. This adaptability was especially advantageous in RPPG analysis, where signals might exhibit dynamic and non-stationary characteristics due to physiological variations or environmental factors.

The superiority of wavelet filtering in RPPG analysis stemmed from its ability to selectively remove noise components while retaining relevant physiological information. By decomposing signals into wavelet coefficients at multiple resolutions, wavelet filters showed robustness to noise and artifacts, enhancing the signal-to-noise ratio and facilitating accurate parameter estimation with more than 92 % confidence.

Moreover, wavelet filtering addressed the challenges encountered with other filtering techniques, such as the bandpass filter, FFT, and Savitzky-Golay filter, which may exhibit limitations in capturing transient components or introducing signal distortions. While deep learning models and Kalman filters offer adaptive processing capabilities, the computational complexity associated with these techniques may pose challenges in real-time applications or resource-constrained environments. In contrast, wavelet filtering provided a computationally efficient solution without sacrificing performance, making it a compelling choice for RPPG analysis.

In conclusion, the wavelet filter is an effective solution for analyzing remote photoplethysmography signals due to its versatility, reliability, and interpretability. By effectively suppressing noise and preserving signal features, wavelet filtering enhances the accuracy and reliability of RPPG analysis, offering valuable insights for clinical diagnosis, physiological monitoring, and research endeavors. This filter reliably produces superior results in RMSE comparisons, with an impressive score of 1.19 bpm. Future advancements in wavelet-based signal processing techniques hold promise for further improving the efficacy and applicability of RPPG analysis in diverse settings.

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