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RESEARCH PAPER

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Robust Real-Time SpO_2 Signal Enhancement Using Optimized IIR Filtering in a Web-Based Vital Sign Monitoring System

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ABSTRACT
SpO_2 is a critical physiological parameter in vital sign monitoring, particularly within Internet of Things (IoT) based healthcare systems that enable continuous and remote patient observation. However, the accuracy of SpO_2 measurements is often compromised by motion artifacts in photoplethysmograph (PPG) signals, which introduce amplitude distortion and frequency spreading that degrade oxygen saturation estimation. Although various signal processing approaches have been proposed, limited studies have evaluated digital filtering performance on real PPG signals using real-time embedded platforms with direct comparison of filter characteristics. This study aims to analyze the effectiveness of two Infinite Impulse Response (IIR) digital filters, Butterworth and Elliptic, in suppressing motion artifacts in SpO_2 signals processed on a microcontroller. Data were collected from ten healthy participants under three conditions: baseline (no movement), induced finger motion, and filtered signals. Signal quality improvement was assessed using Fast Fourier Transform (FFT), Power Spectral Density (PSD), and Signal-to-Noise Ratio (SNR) analyses. Results indicate that motion artifacts increase high-frequency components above 3 Hz and disrupt the morphological integrity of the PPG waveform. Applying a low-pass IIR filter with a 3 Hz cutoff frequency successfully restored the principal periodic components. The Butterworth filter produced a smoother spectral response with minimal phase distortion, while the Elliptic filter achieved a sharper roll-off with slight passband ripple. Quantitative evaluation demonstrated average SNR improvements of +0.905 dB (Butterworth) and +0.899 dB (Elliptic) using FFT , and +0.98 dB and +0.66 dB, respectively, using PSD. These findings demonstrate that computationally efficient IIR filtering can be reliably implemented in resource-constrained embedded platforms without compromising signal integrity. This approach enhances signal stability, reduces false desaturation alarms, supports scalable deployment in wearable and telemedicine applications, improving patient safety and system robustness in continuous remote health monitoring.

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1. INTRODUCTION
Vital sign monitors are an important device for monitoring the patient's physiological condition in real-time, including blood oxygen saturation or SpO_2. This parameter indicates the percentage of oxygen-bound hemoglobin to the total hemoglobin in arterial blood[1][2]. SpO_2 is an important indicator for detecting respiratory and circulatory disorders such as hypoxemia, sleep apnea, and heart failure[3][5][6]. Normal SpO_2 values range from 95–100%[7], and the human brain consumes about 20% of the body's total oxygen[8]. Therefore, an undetected decrease in oxygen saturation can lead to fatal conditions such as silent hypoxemia[9][10]. Silent hypoxemia is particularly dangerous because patients may not show early respiratory distress, leading to delayed diagnosis and treatment. Saturation estimation errors, whether underestimation or overestimation, can result in clinical misjudgment, missed hypoxemia, and increased risk of morbidity and mortality in critical or remote healthcare settings [9][10]. Non-invasive SpO_2 measurement using red and infrared LED-based photoplethysmograph (PPG) sensors. However, PPG signals are particularly susceptible to external interference, such as motion artifacts due to finger movements, lighting variations, and

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electromagnetic interference, which lead to signal distortion and saturation estimation errors [11][12][13][14]. To obtain accurate SpO_2 values, the signal needs to be processed and filtered so that the AC and DC components can be separated[15][16][17][21]. Digital filters, especially Infinite Impulse Response (IIR), are widely used because they are computationally efficient and flexible in the application of microcontroller systems such as Arduino or ESP[13][14]. The Butterworth type is known to have a smooth frequency response, while the Elliptic offers sharp transitions yet with ripples[22][23].

Beyond digital filtering, a number of studies have explored different artifact reduction strategies with distinct strengths and weaknesses. Lee et al. [11] employed multi-channel PPG sensing, which improves artifact separation but increases sensor complexity and cost. Chowdhury et al. [37] applied adaptive filtering cascaded with RNNs, achieving robust heart rate estimation under strong motion, but the method requires high computational resources, unsuitable for low-power microcontrollers. Rao et al. [29] utilized wavelet-based denoising, offering good time frequency localization but introducing latency and requiring parameter tuning. Zargari et al. [27] proposed CycleGAN for artifact removal without reference sensors, achieving high accuracy but relying on large training datasets and GPUs. Gautam and Jebelli [38] applied autoencoders to improve signal reliability but did not address real-time processing constraints. Argüello Prada and Castillo García [39] reviewed machine learning methods that perform well in artifact detection but often lack interpretability and demand high data diversity for generalization. These studies collectively highlight the trade-offs between signal quality improvement and practical deployability in embedded systems.

Various approaches have been developed to improve the quality of PPG signals. Cassani et al. (2020) and Mejía-Mejía et al. (2021) used digital filters to improve pulse rate estimation and variability[24], [25]. Pollreisz and TaheriNejad (2022) implemented an accelerometer-based motion artifact detection algorithm[26], while Zargari et al. (2023) propose the CycleGAN method without additional censorship[27]. Pandi and Abuzairi (2024) analyze analog filters on LTspice simulations[28], while Rao et al. (2024) utilize the Wavelet Transform as a Noise Reference[29]. Lapitan et al. (2024) highlights phase distortion due to IIR filters, but has not evaluated their impact on oxygen saturation estimates[30]. An HTML locally-host system was also developed by Wisana et al. (2024), However, it still uses a reflection method that is not optimal[31].

Despite these advances, several issues remain unresolved. First, most existing work focuses on heart rate estimation rather than on saturation accuracy, leaving the impact of artifact suppression techniques on SpO_2 estimation underexplored. Second, many studies rely on controlled or simulated motion scenarios, which may not reflect real-world variability. Third, approaches using deep learning or complex adaptive filters often have high computational demands that are incompatible with lightweight embedded platforms used in low-cost monitoring devices. Finally, while several filtering methods have been applied individually, there has been no comprehensive comparative analysis of different IIR filter types, specifically Butterworth and Elliptic, under realistic motion artifact conditions. This leaves a clear methodological and implementation gap for practical, real-time SpO_2 monitoring.

Based on this gap, this study aims to analyze the effectiveness of two types of IIR filters, namely Butterworth and Elliptic, in reducing motion artifact noise in SpO_2 signals. The filtered signals were analyzed using Fast Fourier Transform (FFT), Power Spectral Density (PSD), and Signal-to-Noise Ratio (SNR). The monitoring system was developed using an Arduino Nano as the filter processor, a Wemos Mega 2560 as the display controller, and an ESP8266 module for web-based data transmission. Data visualization was carried out both locally through a TFT LCD and remotely via a web interface. Specifically, this study fills the research gap by performing a direct, quantitative comparison of Butterworth and Elliptic IIR filters under actual motion disturbances, focusing on their influence on SpO_2 estimation accuracy rather than on heart rate alone. The implementation on low-power embedded hardware further addresses practical constraints faced in remote healthcare and telemedicine scenarios.

The key contributions of this study are as follows:

- Development of a real-time system: This research presents a functional and low-cost web-based vital sign monitoring platform capable of performing real-time filtering and visualization of raw SpO_2 signals affected by motion artifacts.
- Comparative filter evaluation: It offers a thorough comparative analysis of Butterworth and Elliptic IIR digital filters under actual motion disturbance conditions, using spectral methods and Signal-to-Noise Ratio (SNR) metrics to evaluate performance.
- Insight into inter-subject variability: The study reveals that the effectiveness of each filter varies across different subjects, highlighting a significant practical challenge in biomedical signal processing.
- Support for remote healthcare applications: With both local and remote display capabilities, the system demonstrates strong potential for use in telemedicine, remote diagnostics, and portable or home-based health monitoring.

This article is structured as follows: Section 2 (Materials and Methods) describes the system architecture, signal acquisition process, and digital filtering implementation. Section 3 (Results) presents the experimental findings and quantitative analysis. Section 4 (Discussion) interprets the results and compares them with related studies. Lastly, Section 5 (Conclusion) summarizes the main findings and outlines suggestions for future improvements. This structure is intended to guide the reader through the technical process and analytical reasoning behind the study. Each section builds upon the previous to provide a coherent understanding of the system's performance and potential clinical relevance.

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2. MATERIALS AND METHODS

A. Devices and System Suites

This system uses a Nellcor DS-100A transmittance-type SpO_2 sensor, consisting of red and infrared LEDs and photodiodes, to receive light signals that have passed through the finger network. The Arduino Nano microcontroller is used to alternately control the LED flame and read the analog signal from the photodiode. The resulting analog signal is then filtered and converted to digital data using the Arduino's built-in ADC at a sampling rate of 240 Hz. The processed data is sent serially to the Wemos Mega 2560, which serves as the main display controller and the link to the web interface. For local display, Nextion's TFT LCD screen is used. Data transmission to the web server is carried out using an ESP8266 module integrated with Wemos Mega, so users can monitor signals and SpO_2 values in real-time through an HTML and JavaScript-based interface.

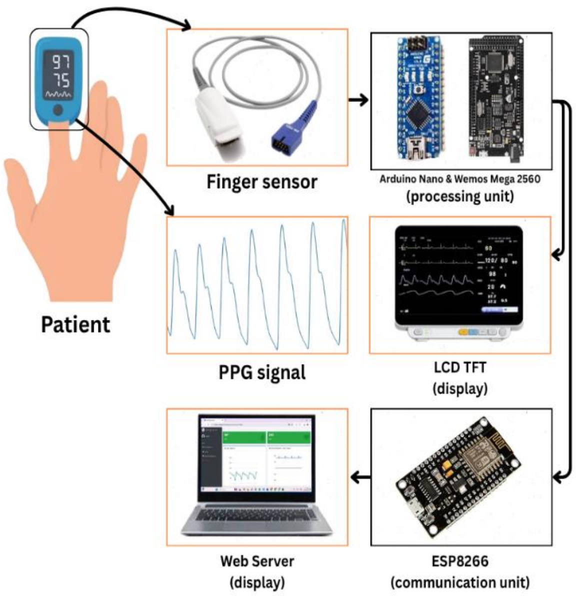

Fig. 1. System Block Diagram

Figure 1 is a block diagram of the system studied, which comprises three main parts: input, process, and output. At the input, the SpO_2 signal is captured by a finger sensor, then amplified and filtered by a series of amplifiers and analog filters, and then read by another Arduino Nano. This Arduino also sets the timing for the red and infrared LEDs used by the SpO_2 sensor. SpO_2 signal processing is fully performed on the Arduino Nano, including the application of digital filters (such as Butterworth and Elliptic) as well as the calculation of oxygen saturation values based on the signal ratio. In the process part, the two Arduino Nano send data via I2C communication to the Wemos Mega 2560, which is the core of the system's processor. Inside the Wemos Mega 2560, it serves as the display and interface control center. The microcontroller determines the type of filter to use (based on user input), displays the results as graphs and numerical values on the TFT screen, and sends data to the ESP8266 for forwarding to the web server over the WiFi network.The output part of the system includes three paths: local display via TFT LCD, data transmission to the web server via ESP8266 integrated in Wemos Mega, and connection to a personal computer for development, display, and data download. This entire data processing and distribution flow is supported by an integrated system based on a web server and web interface design.

B. Digital Filter Implementation

Digital filters, particularly Infinite Impulse Response (IIR) filters, are widely used in biomedical signal processing because of their recursive structure, which allows efficient real-time implementation with lower filter orders compared to Finite Impulse Response (FIR) filters [23]. The general difference equation of an IIR filter can be expressed as:

$$y(m) = \sum_{k=1}^{N} a_k y(m-k) + \sum_{k=0}^{M} b_k x(m-k) \quad (1)$$

where $x(m)$ in Eq.(1) is the input signal, $y(m)$is the output signal, and $a_k$and $b_k$are the feedback and feedforward coefficients, respectively.

Among IIR filter types, the Butterworth and Elliptic filters are frequently used because of their distinct frequency response characteristics. The Butterworth filter is known for its maximally flat magnitude response at zero frequency, with no ripple in either the passband or the stopband. The magnitude squared response of a low-pass Butterworth filter is given by [23]:

$$|H(j\omega)|^2 = \frac{1}{\sqrt{1+\left(\frac{\omega}{\omega_c}\right)^{2N}}} \quad (2)$$

where ω_c in Eq. (2) is the cutoff frequency and N is the filter order. In contrast, the Elliptic filter provides a sharper transition between the passband and stopband with lower filter order, but introduces ripples in both bands. Its magnitude response is expressed as:

$$H(j\omega) = \frac{1}{\sqrt{1+\epsilon^2 R_N^2(\frac{\omega}{\omega_p})}} \quad (3)$$

where ϵ in Eq. (3) is the ripple factor and R_N is the Nth-order elliptic rational function. These theoretical characteristics provide the basis for the filtering strategy employed in this study. To reduce the noise of motion artifacts in photoplethysmograph (PPG) signals, two types of Infinite Impulse Response (IIR) filters are used, namely Butterworth and Elliptic. Both are applied as low-pass filters (LPF) with a cutoff frequency of 3 Hz. This frequency was chosen because it still includes the main component of the SpO_2 physiological signal, while being able to reduce noise from movements that are generally above that frequency. This approach is similar to that taken by Islam et al. (2017), that uses a cutoff range of 0.4–3.5 Hz to filter the PPG signal from the motion artifact [32]. The Butterworth filter was chosen for its smooth frequency response without ripples, while the Elliptic filter offers sharper transitions but introduces ripples in the passband and stopband. The filter implementation is

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carried out digitally using discrete equation-based programming on the Arduino Nano with a fixed-point number approach for computing efficiency

C. Data Acquisition and Delivery

The data used in this study were obtained from ten healthy human respondents (aged 20–30 years) under two measurement conditions: normal (no movement) and light finger movement to simulate motion artifacts. The measurements were carried out using a fingertip SpO_2 sensor attached to the index finger in an indoor setting with stable lighting and temperature. Each condition was recorded for approximately 30 seconds. During the measurement process, the Arduino Nano alternately turns on the red and infrared LEDs. The analogue signal from the photodiode is read at a sampling rate of 240 Hz and processed to obtain the AC and DC components of the respective wavelength. The SpO_2 value is calculated using the AC/DC ratio method with the formula:

$$\mathrm{R} = \frac{(\mathrm{ACRED}/\mathrm{DCRED})}{(\mathrm{ACIR}/\mathrm{DCIR})} \tag{4}$$

$$\mathrm{SpO_2} = 110 - 25 \cdot \mathrm{R} \tag{5}$$

In Eq. (4) above, ACRED and ACIR are the pulse signal amplitudes (AC components) of red and infrared LEDs, while DCRED and DCIR are the average values of the signal (DC components) respectively. The R-value represents the ratio of light absorption by oxygenhemoglobin (HbO_2) and deoxyhemoglobin (Hb), and is used in linear regression models to estimate the percentage of oxygen saturation in the blood as in Eq. (5) The equation is a common approach that is widely used in commercial pulse oximeter devices and previous research. It serves as a standardized method to evaluate signal integrity and is particularly valuable in assessing the impact of digital filtering on noise suppression. Because of its simplicity and effectiveness, the equation has been integrated into both clinical-grade and low-cost wearable systems. In recent literature, it is frequently employed to compare the performance of various filter designs, signal enhancement algorithms, and sensor configurations under different motion and ambient conditions. [2], [15].

D. Data Analysis

Signal quality analysis is performed using MATLAB software. Two types of analysis were used, namely Fast Fourier Transform (FFT) to observe signal characteristics in the frequency domain, and Power Spectral Density (PSD) to evaluate the energy distribution of the signal. Next, a Signal-to-Noise Ratio (SNR) calculation was carried out to assess the effectiveness of the filter in improving signal quality. The test was conducted on 10 respondents under two conditions: normal (no movement) and light finger movement. The SNR value is calculated using the formula:

$$SNR = 10 \times \log 10 \times \left(\frac{Psignal}{Pnoise}\right) \tag{6}$$

In Eq. (6), Psignal represents the total power of the desired physiological component of the photoplethysmographic (PPG) signal, which is primarily concentrated within the frequency range of ≤3 Hz. This threshold is based on the typical spectral distribution of PPG signals, where most of the cardiac-related activity (i.e., the pulsatile component) lies well below 3 Hz, corresponding to heart rates up to approximately 180 beats per minute. Conversely, Pnoise denotes the total signal power found in the frequency components above 3 Hz. These higher-frequency components are typically dominated by unwanted noise such as motion artifacts, ambient light interference, electronic noise, and muscle tremors that do not reflect actual physiological activity. By isolating the energy within and beyond the 3 Hz threshold, Eq. (6) provides a means to quantitatively distinguish between meaningful signal content and noise. The resulting SNR value, expressed in decibels (dB), is the ratio of physiological signal power to noise power on a logarithmic scale, with higher values indicating better signal fidelity. Within this study, SNR is not only used as a general indicator of signal quality but also serves as a critical metric for evaluating the performance of the implemented digital filters. The improvement in SNR before and after filtering is taken as the main criterion to assess how effectively each filter type, specifically the Butterworth and Elliptic Infinite Impulse Response (IIR) filters, suppresses noise while preserving the physiological information. The quantitative results of the SNR improvement (ΔSNR) obtained using both FFT and PSD methods are presented in Table 1.

Table 1. Delta SNR results of each filter using the FFT and PSD methods, before, and After Digital Filtering with the Butterworth Filter and the Elliptic Filter.

Analysis Method	ΔSNR Butterworth (dB)	ΔSNR Elliptic (dB)
FFT	+0.905	+0.899
PSD	+0.601	+0.802

Table 1 shows that both filters improve signal quality. The Butterworth filter slightly outperforms the Elliptic filter in FFT analysis (+0.905 dB vs. +0.899 dB), while the Elliptic filter performs better in PSD analysis (+0.802 dB vs. +0.601 dB). This indicates that filter performance depends on the analysis method and signal characteristics. Overall, both filters effectively enhance SNR, demonstrating their ability to reduce noise in PPG signals and support reliable wearable monitoring applications.

3. RESULTS

The SpO_2 signal analysis was performed using Fast Fourier Transform (FFT), Power Spectral Density (PSD), and Signal-to-Noise Ratio (SNR) in order to assess the ability of Butterworth and Elliptic IIR filters to suppress motion-induced artifacts. Across all ten subjects (n = 10), the unfiltered signals exhibited spectral spreading above

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3 Hz, indicating substantial high-frequency noise generated by finger movements. After applying the filters, the spectral energy became concentrated within the physiological frequency range of 1–2 Hz, which corresponds to cardiac pulsations. The Butterworth filter yielded a smoother spectral roll-off, while the Elliptic filter demonstrated a sharper cutoff response, although with slight passband ripple as a trade-off. The FFT results illustrating these changes are presented. Fig. 2 shows the results of the FFT of the SpO_2 signal before and after filtering using Butterworth and Elliptic filters.

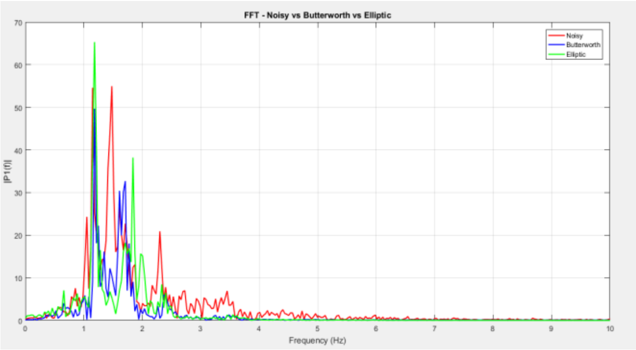

Fig. 2 FFT results of SpO_2 signals before and after filtering using Butterworth and Elliptic filters

The analysis using Power Spectral Density (PSD) further supports the FFT findings. Prior to filtering, the signal exhibited a dispersed and unstable power distribution, indicating the presence of non-physiological high-frequency components. After filtering, the power becomes predominantly concentrated below 3 Hz, confirming that both filters are effective in suppressing noise outside the expected cardiac frequency range. Quantitatively, the Butterworth filter achieved an average SNR improvement of +0.91 ± 0.18 dB (FFT-based) and +0.60 ± 0.21 dB (PSD-based), while the Elliptic filter achieved +0.90 ± 0.16 dB (FFT-based) and +0.80 ± 0.24 dB (PSD-based). Although these improvements remain modest, the consistent positive trend across all subjects demonstrates measurable benefits in mitigating motion artifacts. Fig. 3 is the result of the PSD of the SpO_2 signal before and after filtering using Butterworth and Elliptic filters.

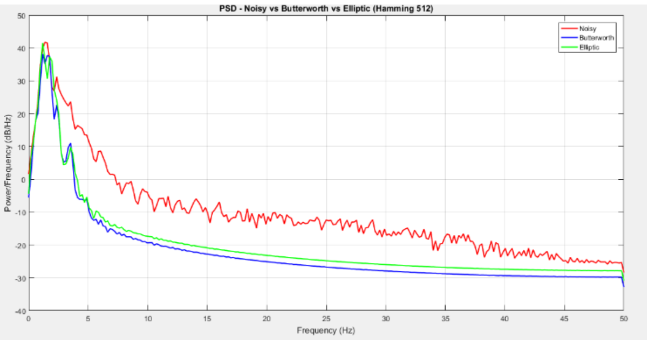

Fig. 3 PSD results of SpO_2 signals before and after filtering using Butterworth and Elliptic filters

Although the SNR improvements are relatively small, the consistent enhancement across all subjects indicates that both filters help reduce motion-induced noise in SpO_2 measurements. The performance differences between the two filters are minor, suggesting that filter selection should be based on application requirements, such as prioritizing waveform stability with Butterworth or achieving sharper cutoff characteristics with Elliptic. These findings provide practical guidance for implementing real-time digital filtering in embedded SpO_2 monitoring systems.

4. DISCUSSION

The aim of this study was to evaluate the effectiveness of Butterworth and Elliptic IIR digital filters in reducing motion artifacts in SpO_2 signals within a web-based monitoring system. Based on the FFT analysis shown in **Fig. 2** and the PSD analyses shown in **Fig. 3**, the unfiltered signals demonstrated spectral spreading above 3 Hz due to finger movement. After applying a 3 Hz low-pass filter, both filters successfully reduced high-frequency noise, and the spectral energy was concentrated within the physiological pulse range of 1–2 Hz, which is essential for maintaining the accuracy of the ratio-of-ratios method used for SpO_2 calculation [33], [34]. The smoother roll-off of the Butterworth filter, visible in **Fig. 2**, helped preserve the PPG waveform, while the sharper transition of the Elliptic filter introduced small ripple in the passband, which may lead to baseline fluctuations over long-term monitoring [24], [25]. Quantitatively, SNR improvements were observed after filtering. The Butterworth filter achieved an average SNR increase of +0.905 dB (FFT-based) and +0.601 dB (PSD-based), while the Elliptic filter provided +0.899 dB (FFT-based) and +0.802 dB (PSD-based). The positive ΔSNR values in **Table 1** indicate that both filters consistently improved the ratio of physiological signal power to noise power across all ten subjects, meaning the filtered signals contain proportionally more cardiac-related information and less motion-induced noise than the unfiltered signals. Although the improvements remain modest in magnitude, the consistent positive trend across all subjects confirms that both filters contributed to reducing motion-induced noise [33] [34]. This variability is consistent with studies such as Zhang et al., which demonstrated that commercial SpO_2 systems, including Masimo, still encounter challenges in motion-artifact suppression, supporting the feasibility of the simpler IIR-based solution used in this system [33].

Similar observations were reported by Cassani et al. (2020) and Mejía-Mejía et al. (2021), who showed that filtering approaches improve pulse estimation but can alter waveform morphology [24], [25]. Lapitan et al. (2024) also highlighted the risk of phase distortion in IIR filters, aligning with the small ripple noted in the Elliptic filter response shown in **Fig. 2** [26]. Compared with accelerometer-based artifact-reduction approaches described by Pollreisz and TaheriNejad (2022), this method requires less hardware complexity while remaining sufficiently effective under low-motion conditions [27], [28].

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Most previous research emphasized output accuracy, such as BPM and SpO_2 values rather than analyzing raw signal integrity. A review by Ghosal et al. reinforced that motion artifacts degrade PPG-based heart rate tracking and highlighted the importance of evaluating noise effects in the frequency domain [35]. In contrast to earlier studies that relied on synthetic or model-based noise, this work uniquely evaluates filtering performance using real human motion artifacts under two activity conditions and includes both spectral and SNR analyses as presented in **Fig. 2**, **Fig. 3**, and **Table 1** [24], [25], [26], [27], [28].

The primary contribution of this study lies in its real-time implementation of Butterworth and Elliptic filters on a low-cost microcontroller system, with visualization on both a local TFT display and a web-based platform. This bridges theoretical digital filter performance with practical deployment in telemedicine systems, emphasizing the importance of maintaining waveform quality for reliable oxygen saturation monitoring [36]. This study has several limitations. Motion artifacts were manually induced and may not represent standardized movement patterns. The sample size was limited (n = 10), reducing the statistical generalizability of results. Furthermore, only fixed low-pass filters were evaluated without comparing adaptive or hybrid filtering strategies that might produce stronger artifact suppression [37][38][39][40]. Despite these limitations, the results demonstrate that digital filtering in embedded systems can improve the reliability of PPG signals in telemedicine and wearable health-monitoring applications.

5. CONCLUSION

This study evaluated the effectiveness of Butterworth and Elliptic IIR digital filters in reducing motion-induced noise in SpO_2 signals for a web-based vital sign monitoring system. Motion artifacts were shown to spread spectral energy above 3 Hz, and applying a 3 Hz low-pass filter successfully concentrated the signal within the physiological frequency range of 1–2 Hz. Quantitative analysis demonstrated modest improvements in SNR, with increases of +0.905 dB and +0.899 dB for Butterworth and Elliptic (FFT-based), and +0.601 dB and +0.802 dB (PSD-based), respectively. System validation using a Contec MS100 simulator yielded an average SpO_2 error of ±2% across the 80–99% saturation and 60–120 BPM ranges, with optimal performance at higher saturation levels.

These findings confirm that both IIR filter types can suppress motion noise, although improvements remain limited and vary across subjects. The Butterworth filter preserved waveform morphology more effectively, while the Elliptic filter provided sharper attenuation at the expense of small passband ripple. Filter selection for real-time SpO_2 monitoring should therefore consider the trade-off between spectral smoothness and cutoff sharpness.

Future research should incorporate statistical hypothesis testing to validate the significance of SNR enhancement, investigate adaptive or hybrid filtering techniques, evaluate a broader range of motion conditions and diverse user profiles, and expand testing to real clinical environments. This work demonstrates the practical feasibility of implementing low-cost digital filtering for remote and embedded oxygen saturation monitoring while highlighting the need for more advanced noise-robust approaches.

REFERENCES

[1] A. Nemcova *et al.*, “Monitoring of heart rate, blood oxygen saturation, and blood pressure using a smartphone,” *Biomed. Signal Process. Control*, vol. 59, p. 101928, 2020, doi: 10.1016/j.bspc.2020.101928.

[2] M. Nitzan, I. Nitzan, and Y. Arieli, “The various oximetric techniques used for the evaluation of blood oxygenation,” *Sensors (Switzerland)*, vol. 20, no. 17, pp. 1–28, 2020, doi: 10.3390/s20174844.

[3] A. Azarbarzin *et al.*, “The Sleep Apnea-Specific Hypoxic Burden Predicts Incident Heart Failure,” *Chest*, vol. 158, no. 2, pp. 739–750, 2020, doi: 10.1016/j.chest.2020.03.053.

[4] K. Adam *et al.*, “Continuous SpO2 Monitoring Using Reflectance Pulse Oximetry at the Wrist and Upper Arm During Overnight Sleep Apnea Recordings,” 2025.

[5] Y. Yeghiazarians *et al.*, “Obstructive Sleep Apnea and Cardiovascular Disease: A Scientific Statement from the American Heart Association,” *Circulation*, vol. 144, no. 3, pp. E56–E67, 2021, doi: 10.1161/CIR.0000000000000988.

[6] Q. Zhang, D. Arney, J. M. Goldman, E. M. Isselbacher, and A. A. Armoundas, “Design implementation and evaluation of a mobile continuous blood oxygen saturation monitoring system,” *Sensors (Switzerland)*, vol. 20, no. 22, pp. 1–11, 2020, doi: 10.3390/s20226581.

[7] R. Sameh, M. Genedy, A. Abdeldayem, and M. H. Abdel Azeem, “Design and Implementation of an SPO2 Based Sensor for Heart Monitoring Using an Android Application,” *J. Phys. Conf. Ser.*, vol. 1447, no. 1, 2020, doi: 10.1088/1742-6596/1447/1/012004.

[8] D. M. Shaw, G. Cabre, and N. Gant, “Hypoxic Hypoxia and Brain Function in Military Aviation: Basic Physiology and Applied Perspectives,” *Front. Physiol.*, vol. 12, no. May, 2021, doi: 10.3389/fphys.2021.665821.

[9] A. Rahman, T. Tabassum, Y. Araf, A. Al Nahid, M. A. Ullah, and M. J. Hosen, “Silent hypoxia in COVID-19: pathomechanism and possible management strategy,” *Mol. Biol. Rep.*, vol. 48, no. 4, pp. 3863–3869, 2021, doi: 10.1007/s11033-021-06358-1.

[10] M. Nakane, “Biological effects of the oxygen molecule in critically ill patients,” *J. Intensive care*,

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vol. 8, no. 95, pp. 1–12, 2020.

[11] J. Lee, M. Kim, H. K. Park, and I. Y. Kim, “Motion artifact reduction in wearable photoplethysmography based on multi-channel sensors with multiple wavelengths,” *Sensors (Switzerland)*, vol. 20, no. 5, 2020, doi: 10.3390/s20051493.

[12] D. Seok, S. Lee, M. Kim, J. Cho, and C. Kim, “Motion Artifact Removal Techniques for Wearable EEG and PPG Sensor Systems,” *Front. Electron.*, vol. 2, no. May, pp. 1–17, 2021, doi: 10.3389/felec.2021.685513.

[13] A. Vito, N. El-Sayes, and K. Mossman, “Hypoxia-Driven Immune Escape in the Tumor Microenvironment,” *Cells*, vol. 9, no. 4, pp. 1–20, 2020, doi: 10.3390/cells9040992.

[14] J. Fine *et al.*, *Sources of inaccuracy in photoplethysmography for continuous cardiovascular monitoring*, vol. 11, no. 4. 2021. doi: 10.3390/bios11040126.

[15] J. Lambert Cause, Á. Solé Morillo, J. C. García-Naranjo, J. Stiens, and B. da Silva, “The Impact of Contact Force on Signal Quality Indices in Photoplethysmography Measurements,” *Appl. Sci.*, vol. 14, no. 13, 2024, doi: 10.3390/app14135704.

[16] J. Park, H. S. Seok, S. S. Kim, and H. Shin, “Photoplethysmogram Analysis and Applications: An Integrative Review,” *Front. Physiol.*, vol. 12, no. March, pp. 1–23, 2022, doi: 10.3389/fphys.2021.808451.

[17] P. Kainan, A. Sinchai, P. Tuwanut, and P. Wardkein, “New pulse oximetry detection based on the light absorbance ratio as determined from amplitude modulation indexes in the time and frequency domains,” *Biomed. Signal Process. Control*, vol. 75, no. December 2021, p. 103627, 2022, doi: 10.1016/j.bspc.2022.103627.

[18] J.-P. Sirkiä, T. Panula, and M. Kaisti, “Investigating the impact of contact pressure on photoplethysmograms,” *Biomed. Eng. Adv.*, vol. 7, no. November 2023, p. 100123, 2024, doi: 10.1016/j.bea.2024.100123.

[19] K. Azudin, K. B. Gan, R. Jaafar, and M. H. Ja’afar, “The Principles of Hearable Photoplethysmography Analysis and Applications in Physiological Monitoring–A Review,” *Sensors*, vol. 23, no. 14, 2023, doi: 10.3390/s23146484.

[20] A. M. Cabanas *et al.*, “Evaluating AI Methods for Pulse Oximetry: Performance, Clinical Accuracy, and Comprehensive Bias Analysis,” *Bioengineering*, vol. 11, no. 11, pp. 1–26, 2024, doi: 10.3390/bioengineering11111061.

[21] J. de Pedro-Carracedo, D. Fuentes-Jimenez, M. F. Cabrera-Umpiérrez, and A. P. González-Marcos, “Structure function in photoplethysmographic signal dynamics for physiological assessment,” *Sci. Rep.*, vol. 15, no. 1, pp. 1–16, 2025, doi: 10.1038/s41598-025-97573-4.

[22] Z. E. Dallalbashi, “MatLab Based Design and Implemetation of Digita Filter,” *JCSNS Int. J. Comput. Sci. Netw. Secur.*, vol. 20, no. October, 2020.

[23] P. Podder, M. Mehedi Hasan, M. Rafiqul Islam, and M. Sayeed, “Design and Implementation of Butterworth, Chebyshev-I and Elliptic Filter for Speech Signal Analysis,” *Int. J. Comput. Appl.*, vol. 98, no. 7, pp. 12–18, 2020, doi: 10.5120/17195-7390.

[24] R. Cassani, A. Tiwari, and T. H. Falk, “Optimal filter characterization for photoplethysmography-based pulse rate and pulse power spectrum estimation,” *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS*, vol. 2020-July, pp. 914–917, 2020, doi: 10.1109/EMBC44109.2020.9175396.

[25] E. Mejia-Mejia, J. M. May, and P. A. Kyriacou, “Effect of Filtering of Photoplethysmography Signals in Pulse Rate Variability Analysis,” *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS*, pp. 5500–5503, 2021, doi: 10.1109/EMBC46164.2021.9629521.

[26] D. Pollreisz and N. TaheriNejad, “Detection and Removal of Motion Artifacts in PPG Signals,” *Mob. Networks Appl.*, vol. 27, no. 2, pp. 728–738, 2022, doi: 10.1007/s11036-019-01323-6.

[27] A. H. Afandizadeh Zargari, S. A. H. Aqajari, H. Khodabandeh, A. Rahmani, and F. Kurdahi, “An Accurate Non-accelerometer-based PPG Motion Artifact Removal Technique using CycleGAN,” *ACM Trans. Comput. Healthc.*, vol. 4, no. 1, 2023, doi: 10.1145/3563949.

[28] Pandi and T. Abuzairi, “Effect of Filters in Photoplethysmography Analog Signals Using Open-Source LTspice Software,” *Int. J. Electr. Comput. Biomed. Eng.*, vol. 2, no. 1, pp. 88–100, 2024, doi: 10.62146/ijecbe.v2i1.32.

[29] B. V. Rao, E. H. Krishna, and K. A. Reddy, “Wavelet Transform Generated Inherent Noise Reference for Adaptive Filtering to De-noise Pulse Oximeter Signals,” *Serbian J. Electr. Eng.*, vol. 21, no. 2, pp. 251–273, 2024, doi: 10.2298/SJEE2402251R.

[30] D. G. Lapitan, D. A. Rogatkin, E. A. Molchanova, and A. P. Tarasov, “Estimation of phase distortions of the photoplethysmographic signal in digital IIR filtering,” *Sci. Rep.*, vol. 14, no. 1, pp. 1–12, 2024, doi: 10.1038/s41598-024-57297-3.

[31] I. D. G. H. Wisana, N. S. Saidah, P. C. Nugraha, M. P. A. Tetra, D. T. Wulandari, and T. Fa’altin, “Wide Communication Coverage SpO2 Monitoring Using Local Host HTML Web Page,” *Lect. Notes Electr. Eng.*, vol. 1182, pp. 235–247, 2024, doi: 10.1007/978-981-97-1463-6_16.

[32] M. T. Islam, I. Zabir, S. T. Ahamed, M. T. Yasar, C. Shahnaz, and S. A. Fattah, “A time-frequency domain approach of heart rate estimation from

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e-ISSN: 2407-8964
p-ISSN: 1907-7904

photoplethysmographic (PPG) signal," *Biomed. Signal Process. Control*, vol. 36, pp. 146–154, 2017, doi: 10.1016/j.bspc.2017.03.020.

[33] T. Yang, Y. Liu, F. H. Cai, Y. Li, and M. S. Mudabbar, "Motion resistance in peripheral oxygen saturation monitoring using Biolight Analog SpO2 compared to Masimo SpO2: a non-inferiority study," *BMC Anesthesiol.*, vol. 24, no. 1, 2024, doi: 10.1186/s12871-024-02823-z.

[34] A. Temko, "Accurate Heart Rate Monitoring during Physical Exercises Using PPG," *IEEE Trans. Biomed. Eng.*, vol. 64, no. 9, pp. 2016–2024, 2017, doi: 10.1109/TBME.2017.2676243.

[35] S. Ismail, U. Akram, and I. Siddiqi, "Heart rate tracking in photoplethysmography signals affected by motion artifacts: a review," *EURASIP J. Adv. Signal Process.*, vol. 2021, no. 1, 2021, doi: 10.1186/s13634-020-00714-2.

[36] P. Zhang, J. Zhuang, T. Li, D. Fan, Q. Lei, and D. Lin, "Comparison of consistency between wireless and conventional wired monitoring systems in gastrointestinal endoscopy," *Sci. Rep.*, vol. 15, no. 1, pp. 1–8, 2025, doi: 10.1038/s41598-025-12927-2.

[37] S. S. Chowdhury, M. S. Hasan, and R. Sharmin, "Robust Heart Rate Estimation from PPG Signals with Intense Motion Artifacts using Cascade of Adaptive Filter and Recurrent Neural Network," *IEEE Reg. 10 Annu. Int. Conf. Proceedings/TENCON*, vol. 2019-Octob, no. October, pp. 1952–1957, 2019, doi: 10.1109/TENCON.2019.8929692.

[38] Y. Gautam and H. Jebelli, "Autoencoder-based Photoplethysmography (PPG) signal reliability enhancement in construction health monitoring," *Autom. Constr.*, vol. 165, no. September 2023, p. 105537, 2024, doi: 10.1016/j.autcon.2024.105537.

[39] E. J. Argüello-Prada and J. F. Castillo García, "Machine Learning Applied to Reference Signal-Less Detection of Motion Artifacts in Photoplethysmographic Signals: A Review," *Sensors*, vol. 24, no. 22, 2024, doi: 10.3390/s24227193.

[40] G. Basso, X. Long, R. Haakma, and R. Vullings, "Reduction of motion artifacts from photoplethysmography signals using learned convolutional sparse coding," pp. 1–23, 2025, [Online]. Available: http://arxiv.org/abs/2508.10805

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