RESEARCH ARTICLE

INTERNATIONAL RESEARCH JOURNAL OF
MULTIDISCIPLINARY TECHNOVATION

Asian Research Association

DOI: 10.54392/irjmt25320

Enhancing Healthcare Monitoring through Wearable Computing and Massive MIMO Technology in 5G IoT Networks

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DOI: https://doi.org/10.54392/irjmt25320
Received: 03-07-2024; Revised: 06-05-2025; Accepted: 16-05-2025; Published: 24-05-2025

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Abstract: The growing need for continuous, real-time monitoring of vital physiological parameters like heart rate and blood pressure is driven by the demand for enhanced healthcare, particularly in remote or critical scenarios. Traditional healthcare systems often struggle with delays, inaccuracies, and high costs, making timely medical interventions more challenging. This study aims to design and implement a portable health monitoring system that use widely available technology and advanced wireless communication to address these issues effectively. The system integrates various sensors to track key physiological metrics and applies biomedical signal acquisition along with pre-processing and feature extraction techniques to reduce noise and improve signal quality. Wireless transmission enables real-time data transfer, supporting remote monitoring and analysis. To enhance communication efficiency, the system incorporates Massive Multiple-Input Multiple-Output (MIMO) technology within 5G Internet of Things (IoT) networks, ensuring higher data transfer speeds, reduced latency, and reliable connectivity. The findings demonstrate notable improvements in signal clarity and data transmission, reflected in a significant boost in Signal-to-Noise Ratio (SNR) and a reduction in Bit Error Rate (BER), underscoring the system's effectiveness. By integrating 5G Massive MIMO technology, the performance of Wireless Body Area Networks (WBANs) is substantially improved, leading to more efficient patient monitoring.

Keywords: Wavelet transform, Channel estimation, Healthcare monitoring, MIMO, WBAN

1. Introduction

The growing global population highlights the pressing necessity for innovative digital healthcare solutions to tackle the increasing health challenges encountered on a global scale. Among these challenges, cardiovascular maladies and a range of chronic conditions emerge as predominant contributors to mortality in numerous nations. There is an increasing need to develop intelligent healthcare systems that enhance efficiency while minimizing costs. Achieving this goal necessitates the creation of a robust network infrastructure capable of supporting advanced technologies such as 5G and Massive MIMO. Integrating these innovations into healthcare systems marks a significant shift in medical services, leading to greater efficiency, better patient outcomes, and reduced expenses. This holistic approach not only addresses the current healthcare demands of a growing population but also lays the groundwork for a sustainable system that can evolve with future advancements in medical science and technology [1].

The arrival of 5G technology means that changes are about to happen in several industries such as automation, communication, transport, agriculture, and most importantly, digital health care. With its quick transmission speed and wide-ranging bandwidth, 5G technology is expected to revolutionize patient care by enabling timely and efficient communication which is extremely crucial in the management of critical healthcare situations. Additionally, the IoT has already impacted countless industries around the globe, leaving a significant mark on the field of digital healthcare. The Internet of Medical Things (IoMT) provides the framework for effortless communication between all physicians, health care institutions and patients which improves the entire process of diagnosis, data processing, and treatment. Combining 5G technology with IoMT opens up opportunities for profound advancements in medicine, especially in regard to critical disease diagnosis, by providing higher dependability and short response time. Moreover, Wireless Body Area Networks (WBANs) play an important role in enabling health care monitoring applications through interconnection of ambient devices for constant surveillance of patients, thus making them crucial to the healthcare field. The development and expansion of 5G technology offers powerful synergies with the IoMT and WBANs which could change the landscape of healthcare delivery. This advancement is marked by improved diagnostic accuracy, customized treatment approaches, and improved overall outcomes [2].

A wide array of devices is integrated into the healthcare system as advanced sensors to collect data. However, this has made it next to impossible to analyze the data via ordinary devices due to its volume. For continuous monitoring and data management, implementing cloud storage and analytical systems has become crucial. On the flip side, relying solely on cloud storage may bring latency challenges which can be detrimental to the efficiency of healthcare interventions. Employing peripheral computation structures is a plausible solution to this issue. Such frameworks lower latency by allowing data processing and analysis to be completed closer to the data collection source, guaranteeing restrictions on time for analyzing a patients' health status [3].

The illustration, as depicted in Figure 1, presents a streamlined wireless healthcare monitoring system displaying the application of edge computing in the data processing strategy. This system manages the growth of wireless monitoring technologies driven by IoT as well as the dynamic growth of sensor technology. Additionally, the advent of 5G communication technologies has catalyzed the production of wireless monitoring solutions, facilitated seamless data transmission and enabled real-time monitoring capabilities. This convergence of IoT, sensor technology, and 5G communication has forced wireless monitoring to the forefront of modern healthcare, offering unprecedented opportunities for remote patient monitoring, early intervention, and personalized healthcare delivery [4].

Timely intervention and appropriate medical advice are highly essential for heart-related problems. Though there are many healthcare devices available in the market, there is a requirement for developing smart and cost-effective healthcare solutions focused towards heart care. In many healthcare monitoring devices, large amounts of data are collected and provided to the users. However, a lot of work is to be done on the data analysis to reveal the critical diseases and falls of elderly people. The availability of machine learning, deep learning and edge computing platforms can be utilized for better and novel solutions. Based on the literature review of healthcare monitoring for critical diseases, many novel solutions are available with a focus on many aspects. However, low-cost and high-accuracy devices have to be developed with the help of intelligent algorithms and affordable powerful computing frameworks. The drawback of the system is less accuracy in heart disease detection and the high cost involved in providing solutions [5, 6].

Wearable devices are developed for heart disease risk detection and analysis based on wireless sensor networks, but real-time observation and accuracy improvement lead to complex operational requirements and high costs. To reduce the cost of wearable devices, a new framework has to be developed [7]. Figure 2 shows the Biosignal acquisition setup for real-time monitoring using sensors, NI LabVIEW and NI MYDAQ. In wearable computing-based wireless monitoring systems, ECG signals are normally interfered with some high-frequency signals due to improper channel conditions [8]. These interferences may degrade the transmitted signal characteristics and make it impossible to perform accurate analysis. In scenarios necessitating Electrocardiogram (ECG) analysis, preprocessing for noise removal is an essential step, particularly in the context of modelling noise as white Gaussian noise.

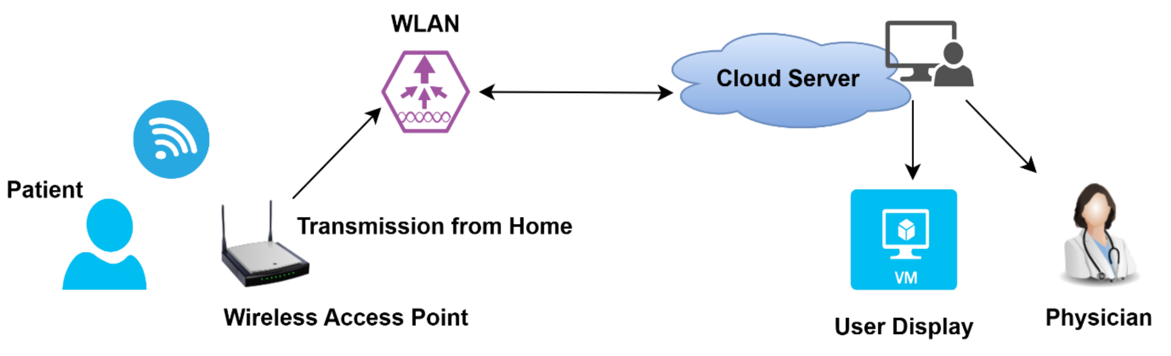

Figure 1. Wearable-enabled wireless healthcare monitoring system

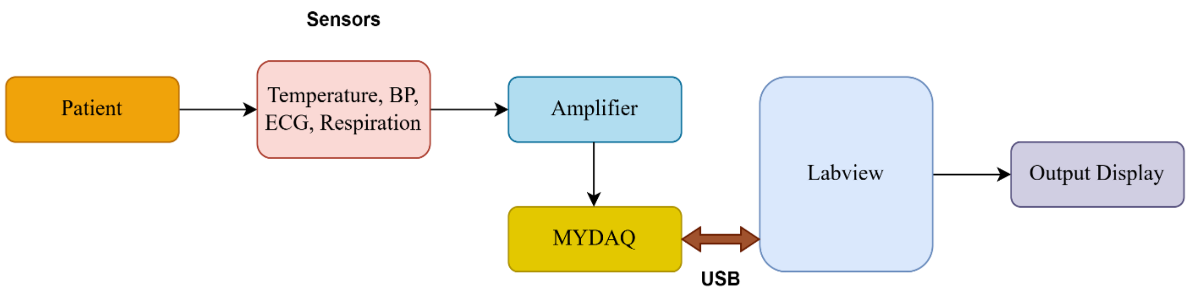

Figure 2. Real-time biosignal acquisition and monitoring

White Gaussian noise is a common source of frequency interference in numerous applications, frequently compromising otherwise pristine electrocardiogram (ECG) signals. To address this challenge, researchers have created specialized wavelet algorithms for denoising, which aim to accurately estimate and counteract the effect of white noise. In this approach, it is important to select a proper wavelet basis function for signal decomposition in order to extract noise components from the primary ECG signal. Later thresholding operations are then applied to help in the reconstruction of the signal and during the process, residual noise is reduced and the signal is made clearer. With advanced ways of eliminating noise, health practitioners and researchers have increased the quality of ECG analysis and, therefore, improved the level of diagnosis and caring for patients [9].

Accomplishing higher data rates and minimal bit errors in wireless communication systems calls for precise channel estimation since there is distortion of the signal during the propagation through the communication channel. There are different methods which are used for determining the state of the channel for the improvement of the quality of transmission. This research seeks to enhance the efficiency of a wireless transmission system based on a wearable computer by applying extensive white noise suppression preprocessing and feature extraction, relaxing the effects of white noise and improving the signal quality. This study intends to develop a more advanced wireless health care system based on ubiquitous computing that is able to accurately and reliably capture physiological information pursuing wavelet based preprocessing techniques [10].

Dynamic tracking of vital parameters is critical in modern health care, particularly in chronic conditions management and prompt treatment delivery. Heartbeat rates, blood pressure, body temperature, ECG, and glucose still remains critical metrics that captures a person's state of health and can further improve patient outcomes if monitored continuously. However, traditional healthcare systems face significant challenges that include high costs, delayed interventions, low data accuracy, and complications with remote patient monitoring. Such challenges are aggravated in cases of emergencies or remote regions where timely healthcare access is limited.

Despite innovations in wearable technologies, real-time monitoring remains difficult due to issues such as connectivity interruptions, restricted data throughput, and excessive signal noise that are most common obstacles today. Additionally, most of the systems rely on conventional communication channels that have low priority and bandwidth and therefore cannot cope with prompt and accurate medical information and insights. While the majority of wearables provide measurements of specific parameters, very few physically integrated multiple indicators and provided real-time monitoring over robust scalable communication systems.

This methodology proposes a solution to these difficulties by adding wearable sensors that track key health metrics in combination with advanced signal processing techniques like wavelet noise filtering and feature extraction. These techniques enhance the quality of the signal such that it can be used for monitoring in real-time. To further increase data speeds, reduce latency, and ensure reliable and constant transmission, the solution employs modern wireless communication, using 5G Massive MIMO technology in IoT networks. This makes it possible for the system to process large amounts of data in real-time, ensuring that monitoring is continuous without delay or loss of accuracy.

1.1 Main Contributions

- The system includes wearable sensors, vital signs monitoring, and filtering using wavelets to enhance signal quality by reducing noise.
- It runs 5G IoT networks using Massive MIMO for fast and low-latency wireless connections, ensuring no data is lost.
- AI/ML algorithms on big data, audaciously known for pattern recognition and advanced signal processing methods (for feature extraction and noise removal) enable swift and accurate health data for timely interventions.
- The architecture of the system allows for scalability that improves the functionality of

WBANs for multiple health services, extending from remote monitoring to inpatient settings.

In addition, the MIMO technology incorporation is being analyzed for its potential to improve communication systems performance. In this section, a comprehensive review of the literature is presented in section two. Wavelets together with the wavelet type signal processing are defined in details in section three. In section four, the processes of biosignal preprocessing and wireless transmission are proposed in relation to the healthcare systems that are based on ubiquitous computing. The results of the preprocessing steps and the results of channel estimation in MIMO communication are clarified in section five, while section six summarizes all the conclusions drawn.

2. Related Works

The integration of ubiquitous computing and Massive MIMO technology into 5G Internet of Things (IoT) networks is crucial for advanced healthcare monitoring. Computers in the form of wearables, fitness trackers, and medical sensors provide health data 24/7. This constant monitoring makes it easy to control and manage chronic conditions. These devices have shown significant promise in advanced patient care by allowing for tailored treatment and remote monitoring, improving overall health care efficiency [11].

Massive MIMO technology has been dubbed the Elementary Technology of fifth generation networks. It improves quality and augments the data transmission speeds by deploying a large number of antennas to the base station. This new technology increases the spectral efficiency and the network capacity which is needed for processing huge amounts of data from millions of connected devices in Internet of Things (IoT) systems. Massive MIMO facilitates controlled mobile communications using the Internet with real-time data transfer and supervision through many interconnected health monitoring gadgets, providing the necessary communication quality to ensure incessant health data flow and real-time analysis [12].

The high data rates and low latency of 5G networks make them exceptionally useful for enabling real-time telemedicine and effective healthcare monitoring. Such advanced networks enable the immediate transfer of crucial health data, which allows for prompt medical action and continuous monitoring of the patient’s vitals. Such instant connectivity is important in remote patient monitoring and telemedicine since rapid data sharing is highly critical for patient care and results, giving health specialists the opportunity to act without any delays [13].

The exceptional merging of ubiquitous computing and Massive MIMO technology into the 5G IoT networks successfully solves multiple problems that modern day healthcare systems face. For example, the MIMO technology integrated with 5G IoT networks has the capability to meet the high bandwidth requirements and low latency needs for healthcare uses that are critical for different service applications. This ensures that the data from peripheral devices is accurately and always sent in a timely manner to the healthcare providers, which allows continuous monitoring and quick action on health issues. Such new technologies make it easier for healthcare centers to improve patient care, enhancing patients’ health and more effective use of medical resources [14].

This integration aids in improved patient monitoring, faster response times, and improvement in the provision of overall healthcare services. The operational aspects of these technologies stand to largely improve data accuracy and decrease the lag time in remote health monitoring for better patient management. Health care professionals are able to make timely and informed decisions because they receive health data from remote devices in a quick and accurate manner. This improves disease management, enables more precise treatment interventions, and allows rapid attention to unscheduled health issues, which improves patient results and healthcare services efficacy [15].

The application of Massive MIMO technology in telemedicine use cases of 5G networks has shown remarkable improvements in data transmission productivity and network reliability. This technology ensures that vast amounts of medical information, including high resolution images and real time video consultations, are transmitted quickly and seamlessly. The improved reliability of the network guarantees that there is no interruption on the connections which is vital for maintaining the standard of telemedicine services. As a result, healthcare providers are able to give more effective and reliable remote consultations, which increase patients’ access to medical services and prompt actions [16].

Integrating new technologies comes with a range of obstacles like data privacy, security, and the need for a strong and effective network infrastructure. Solving these problems is crucial for the problems is crucial for the broader application of these technologies in the health care industry. Future studies should focus on developing secure communication protocols and effective health information management systems within 5G IoT networks to protect sensitive data. There is considerable difficulty in completing these processes due to the data privacy obstacles. However, utilizing ubiquitous computing and MIMO technology in 5G IoT networks can further the development of monitoring systems for the health care industry. Having these integrated can drastically improve patient monitoring by providing real time data transfer and network improvement [17].

The use of artificial intelligence and the Internet of Things has greatly changed the workflows in the healthcare sector and therefore has created a chance to come up with better, smarter and scalable solutions. The DT-LSMAS: Digital Twin-Assisted Large-Scale Multiagent System for Healthcare Workflows is a digital twin infrastructure that is meant to improve the performance of healthcare operations in multiagent systems. Likewise, the Fiber-Optics Internet of Things (IoT) Healthcare System: Design, Implementation, and Evaluation of Deep Reinforcement Learning for Combinatorial Constraint Scheduling in Hybrid Telemedicine Applications, uses deep reinforcement learning in conjunction with fiber optic IoT technology to improve the performance of telemedicine services. Furthermore, the Federated Reinforcement Learning-Assisted IoT Consumer System for Kidney Disease Imaging uses federated learning and reinforcement learning to permit secure processing of medical images. Therefore, the Digital Healthcare Framework for Patients with Disabilities developed based on Deep Federated Learning can help people with disabilities in getting access to the healthcare services by using the advanced deep federated learning approaches. In conclusion, these studies reflect the importance of artificial intelligence, the Internet of Things, and federated learning in the evolution of intelligent and patient-focused healthcare systems.

3. Wavelet-based ECG Signal Processing

The wavelet transform (WT) is especially advantageous for the analysis of non-stationary signals in comparison to alternative transforms. It is frequently favored for the analysis of diverse biomedical signals. This section presents a comprehensive review of wavelet transforms, examines the implementation of discrete wavelet transforms, and investigates the application of wavelet techniques in the processing of electrocardiogram (ECG) signals.

3.1. Wavelet Transform

Wavelet analysis is favoured in many real-time signal processing applications to address the limitations of the Fourier transform. In this work, wavelet techniques are employed to determine heart rate from ECG signals. While the Fourier Transform (FT) represents a signal in the frequency domain, it lacks time information. Wavelets, which are small waves localized in both time and frequency through scaling and shifting functions, overcome this limitation. Wavelet Transform (WT) offers multi-resolution analysis, yielding a few important signal coefficients. Wavelets are used as basis functions, similar to the sines and cosines in the Fourier Transform (FT), for representing functions$f(t)$.

$$f(t) = \sum_k a_k \psi_k(t) \tag{1}$$

A signal is divided into its basic functions of time and scale using the WT. These functions are translated and expanded versions of a main function called the mother wavelet.

$$\psi s, \tau(t) = \frac{1}{\sqrt{s}} \psi(\frac{(t-\tau)}{s}) \tag{2}$$

Where s is the scale factor and τ represents the translation factor.

The discrete wavelet transform (DWT) differs functionally from the continuous wavelet transform (CWT), with the latter being more suitable for multi-resolution analysis of biomedical signals. The CWT of the signal f (t) is expressed as

$$C(\tau, s) = \frac{1}{\sqrt{s}} \int_t f(t) \psi^* \left(\frac{t-\tau}{s}\right) dt \tag{3}$$

The DWT of the signal $f(t)$ is given as

$$a_{jk} = \sum_t f(t) \psi_{jk}^*(t) \tag{4}$$

In Equation (4) * represents complex conjugation which illustrates the decomposition of a function f (t) into a series of basis functions. The expression for the inverse discrete wavelet transform of the signal $f(t)$ can be formulated as

$$f(t) = \sum_k \sum_j a_{jk} \psi_{jk}(t) \tag{5}$$

Wavelet analysis provides a solution for surpassing the constraints of the Fourier Transform (FT) when conducting multi-resolution analysis of biomedical signals.

3.1.1. Wavelet Decomposition and Reconstruction

The DWT implementation uses discrete filter banks to calculate discrete wavelet coefficients. In biological signal processing applications, DWT is used to find intricate time-frequency connections. When it comes to DWT, the decomposed time series performs better than the original. The wavelet transform's decomposition and reconstruction procedures are shown in Figure 3. The resulting subbands, $y_0\ (n)\ or\ y_1\ (n)$, can be downsampled without losing information because their bandwidth is less than that of the original signal, $x(n)$.

Wavelet reconstruction has three steps: upsampling, filtering, and decomposition, which involves high-pass and low-pass filtering in addition to downsampling. These techniques of wavelet decomposition and reconstruction prove valuable for denoising and feature extraction in ECG signals. The recorded ECG signal undergoes decomposition, and the decomposed samples are then processed using adaptive threshold values. This procedure is illustrated in Figure 4. In multi-resolution analysis (MRA), mother wavelets are utilized to create orthonormal bases.

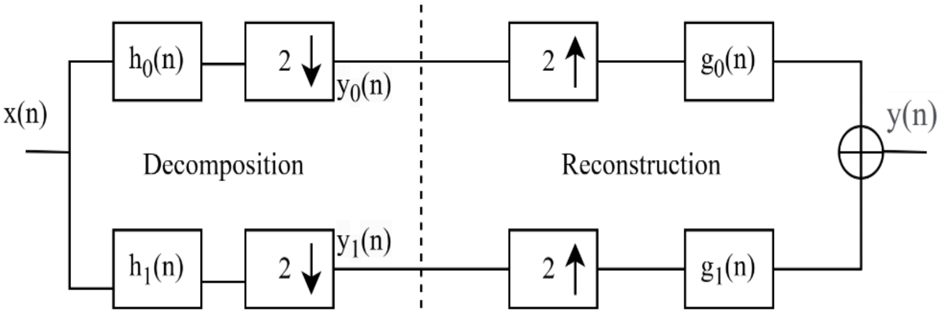

Figure 3. Wavelet-based signal decomposition and reconstruction

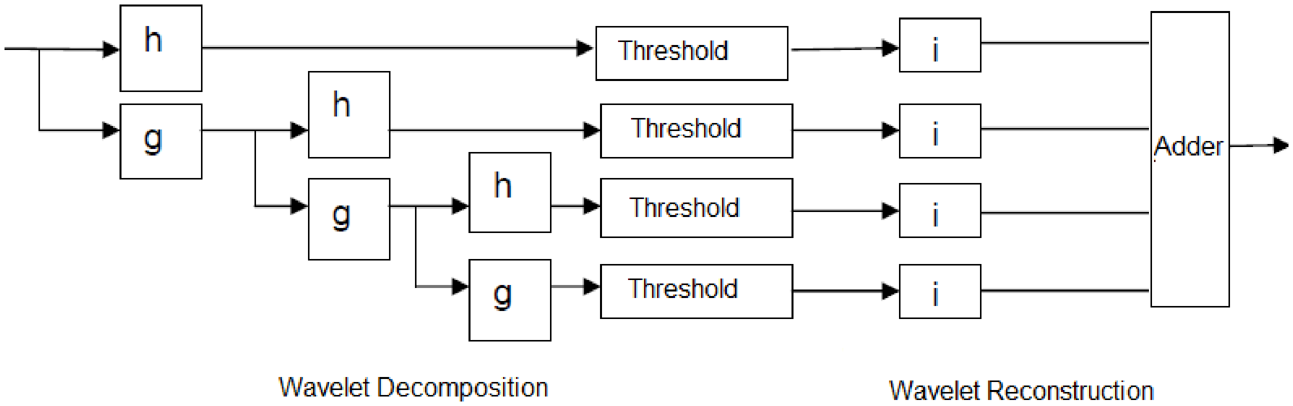

Figure 4. Decomposition and reconstruction with threshold

The Meyer wavelet, a symmetric orthogonal wavelet, defines both its scaling function and wavelet in the frequency domain. A Meyer wavelet neural network has been employed to eliminate noise and extract features from ECG signals [18].

Biorthogonal wavelets display linear phase characteristics, essential for signal reconstruction. Utilizing two wavelets in decomposition and reconstruction allows for extracting crucial features from ECG signals. Biorthogonal wavelets offer additional degrees of freedom compared to orthogonal wavelets. Coiflets represent another category of wavelets derived from the Daubechies wavelet, known for their increased symmetry and nearly linear phase characteristics. Coiflets are often preferred over Daubechies and Spline wavelets in many biosignal processing applications [19].

3.1.2. Wavelet-Based ECG Signal Processing

The methods for detecting R-peaks and eliminating noise from ECG using Wavelets is important for wearable computing devices. The ECG signal is decomposed with the help of wavelet transformation and provides its detailed and approximate coefficients with respect to a wide range of frequencies. This is followed by denoising, where the decomposed coefficients filtered for unneeded signal components. Then, analysis on the cleaned-up/ noise-free ECG signal is performed to extract all potential R-peaks; R-peaks play a significant contribution towards the improvement of patients' diagnosis in health care applications. In Figure 5, the steps of R-peak detection from noisy ECG signal are explained. In this paper, Haar, Db4, Db6, Db8, and Db10 wavelets are used to remove noise from ECG signals, whereas Symlet and Coiflet wavelets are used for detecting the QRS complex and R-peaks in this study [20].

Continuous monitoring and evaluation of biological signals are highly significant in ubiquitous biomedical devices. In this work, we propose a noise removal process of electrocardiogram (ECG) signals through wavelet packet transform, as well as R-peaks detection using wavelet features extraction. It is an extension of two dimensional wavelets with high frequency resolution unlike traditional wavelet decomposition. An overlapping approach is applied in order to identify R-peaks in the ECG signal which allows to calculate heart rate. Time between R-peaks are used to characterize signal morphology and compute heart rate in beats per minute (bpm). R-peak detection plays a vital role in calculating the correct heart rate while identifying the arrhythmias or several other chronic cardiovascular diseases.

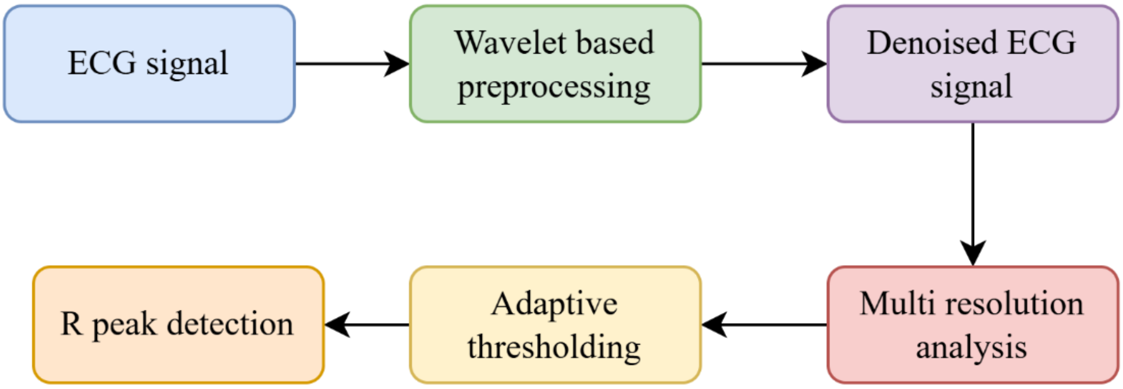

Figure 5. Wavelet-based ECG de noising and feature extraction for R-peak detection

Using different threshold values based on the level of decomposition leads to better performance of noise reduction. The decomposition tree is used to suppress wavelet coefficients, leading to a better temporal resolution. Considering the crucial significance of heart rate in the development of biomedical signal applications, this study seeks to improve the precision of heart rate measurement derived from continuously monitored electrocardiogram (ECG) signals [21].

The primary reason for utilizing a wavelet-based R-peak detection method is its minimal complexity. This method is dependent on heart rate function and RR intervals. By dividing one minute by the instant heart rate, the heart rate function calculates the RR interval. It first calculates the initial interval and then uses this function to calculate the subsequent interval. Meyer, biorthogonal, and coiflet wavelets were selected.

For this investigation because of their track record of success in identifying QRS complexes in ECG signals. It is possible to improve peak identification and reduce noise by employing a nonlinear combination of wavelet coefficients. The multi-scaled product makes it easier to choose wavelet filter banks that will allow you to accurately detect the QRS complex and reconstruct the ECG signal noise-free [22].

4. Proposed Wearable Computing Framework

Biomedical signal acquisition and its processing are preliminary steps in developing a portable biomedical device. ECG noise removal and feature extraction are performed in this wearable computing-based wireless transmission system for removing white noise and improving signal quality. This work addresses the important heart care monitoring and wireless transmission with channel estimation. Cloud computing framework is available to store collected data from wearables and perform necessary computations. Wavelet-based analysis is performed for ECG noise removal and desired feature extraction. The proposed idea provides better performance and improved accuracy in heart disease detection and prediction. The proposed methodology is structured into three major action plans:

(i) ***Data Collection:*** Various sensors are deployed in the wearable device to monitor the heart rate, blood pressure, and body temperature. Passive infrared (PIR) motion sensors are best suited to this work. Unobtrusive MEMS-based wearable devices could be used in a few circumstances. Heart rate variability (HRV) data are collected through wearable ECG devices. HRV is useful in the analysis of heart-related problems and is also helpful in fall detection. Data collection is also possible with wearable devices available in the market.

(ii) ***Data Storage and Computing Framework:*** The huge volumes of collected data have to be stored in the cloud server for further processing. The Internet of Healthcare Things focuses on performing computing tasks near the source, referred to as the edge of things.

(iii) Channel estimation is a technique used in wireless communications to maximize bit error reduction while maintaining a high data throughput. Due to the circumstances of the channel, signals are typically distorted as they travel across it. The status of the channel is ascertained by a variety of methods in channel estimate.

Figure 6 shows the proposed wearable computing framework for developing a wireless healthcare system with continuous biosignal monitoring. ECG signal acquisition and other physiological signal recording are performed through sensors. ECG signal acquisition comprises front-end circuits and processing chips.

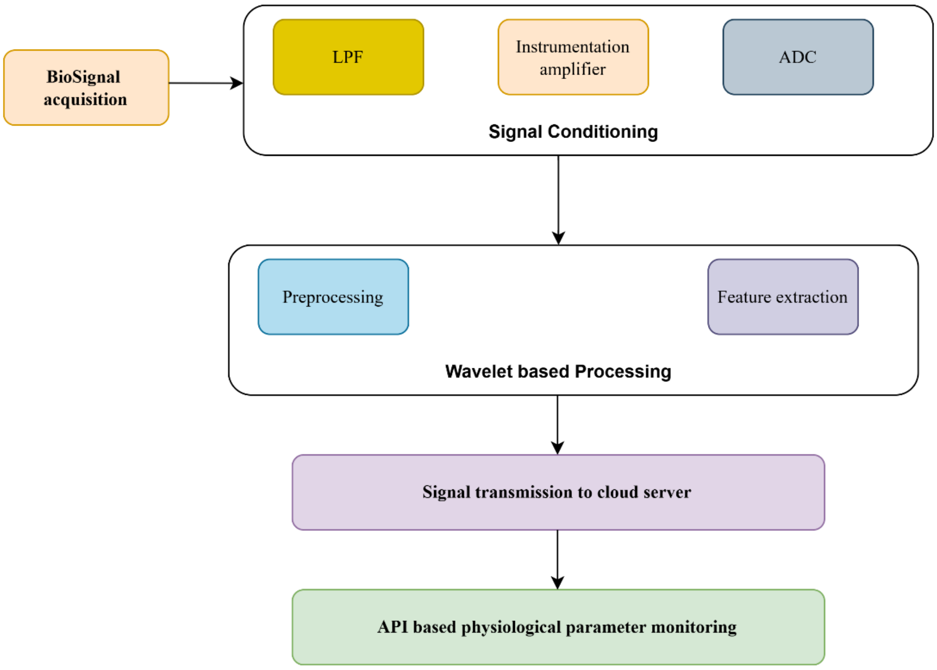

Figure 6. Proposed wearable computing framework

The analogue front end with LPF, instrumentation amplifier and ADC is responsible for signal conditioning of the ECG signal.

Though the signal acquisition is done by analogue front-end circuits, signal processing tasks are accomplished by internal signal processing circuits. Fig. 6 shows the ECG acquisition frond end block diagram, which receives the signal through electrodes and sends the signal to the back-end processing circuits. The important elements are Low Pass Filter (LPF), Instrumentation amplifier, ADC and RF transmitter.

The human ECG signal must be increased before being used as a filter input because its initial amplitude is only a few millivolts. High-pass filters are used to remove DC signals from signals before applying the cleaned signal to the instrumentation amplifier. Given that the range of frequencies for most ECG signals is between 0.1 and 150 Hz. Therefore, it is imperative to exclude the frequency range above 150 Hz. Tran's conductance amplifier-based filters are used to prevent leakage and reduce power consumption.

To eliminate power line interference, in addition to the LPF, a 50 Hz notch filter is employed.

The ECG monitoring system has circuits for radio frequency transmitters that allow for wireless healthcare monitoring. Power amplifiers and double balance-up conversion mixers work together to reduce power usage. It lowers the output power needed by the local oscillator and isolates the radio frequency (RF). The designed module can be connected over the internet to any mobile device because it has WiFi enabled. The studied results will be visualized on a mobile phone through the use of an Application Programming Interface (API). The parameters of the algorithms used in the study are Haar, Db4, Db6, Db8, Db10, Symlet, and Coiflet wavelets.

Some MIMO-based channel estimation methods are taken into consideration for comparison. Several pilot-based and blind estimating strategies are taken into consideration while calculating bit error rate (BER) and normalized mean square error (NMSE) for various signal-to-noise ratio (SNR) values. Several channel estimation methods, such as Least Square Error (LSE), Minimum Mean Square Error (MMSE), and Best Linear Unbiased Estimation Algorithm (BLUE), use a pilot to determine the channel state.

5. Results and Discussion

The results were obtained using Matlab 2023a with the Signal Processing Toolbox, Filter Design Toolbox, and Communication System Toolbox. Performance analysis of wavelet-based signal preprocessing and feature extraction was conducted using the MIT-BIH Arrhythmia Database. Figures 7, 8, and 9 show the results of ECG decomposition for noise removal using bi-orthogonal, Symmlet and Meyer wavelets. All denoising results were achieved with level 5 decomposition to maximize SNR. Although SNR increases with higher decomposition levels, there is no significant improvement beyond level 5 in this study. Table 1 presents the SNR values for various wavelets at different decomposition levels. The Meyer wavelet yielded a superior ECG signal quality with an SNR of 45.74 dB, representing a 14.7% improvement over the biorthogonal wavelet.

From Figures 7, 8 and 9, it is observed that the morphology of the ECG signal is slightly different from one to another. Due to the variation in denoising, it may affect the beat rate estimation which is crucial in HRV feature extraction. The denoised ECG is applied into the R-peak detection stage to determine the beats per minute (bpm). Since the human heart rate values vary between 60 to 100 bpm, it is expected to produce several beats in the acceptable range. However, few wavelets provided a beat rate above 100 bpm.

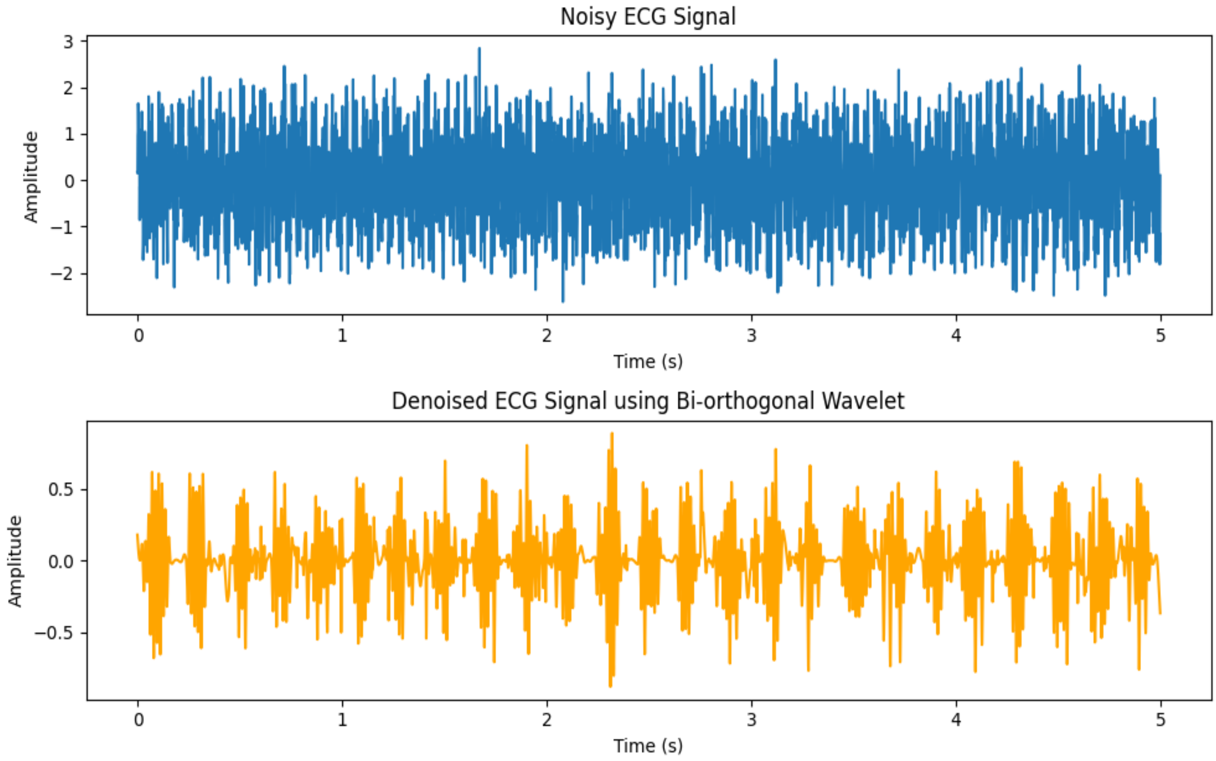

Figure 7. Original and denoised ECG signal using bi-orthogonal wavelet

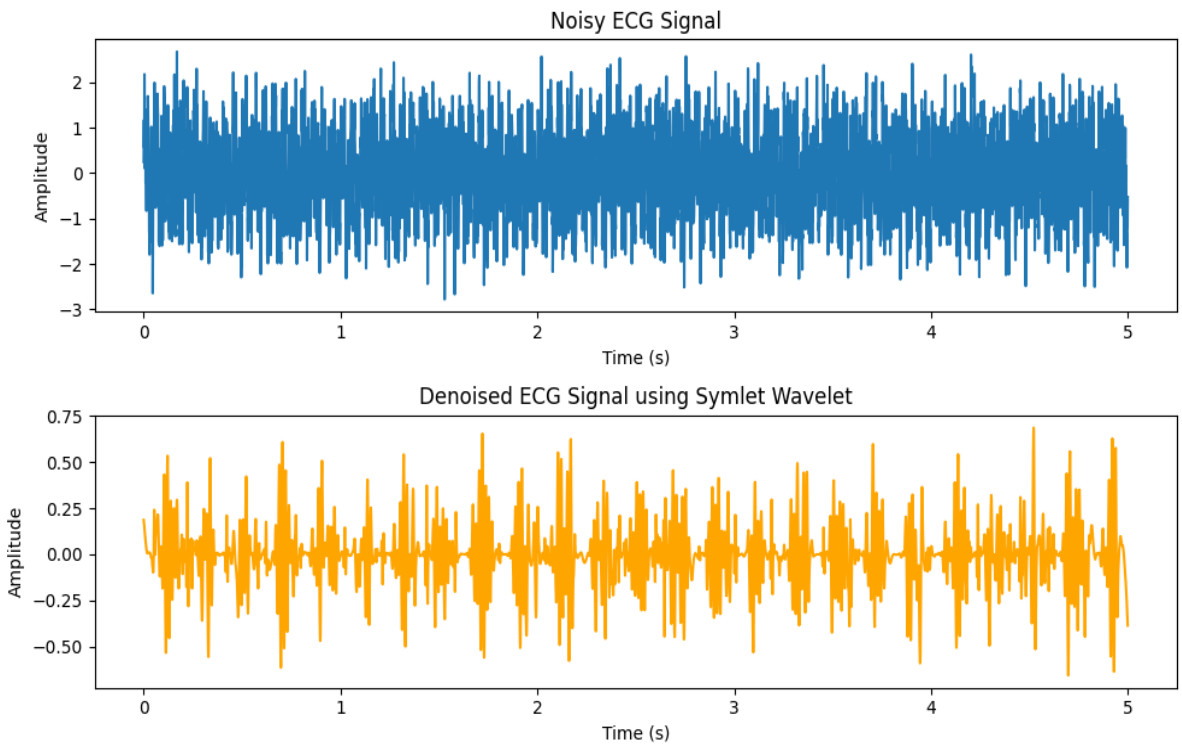

Figure 8. Original and denoised ECG signal using Symmlet wavelet

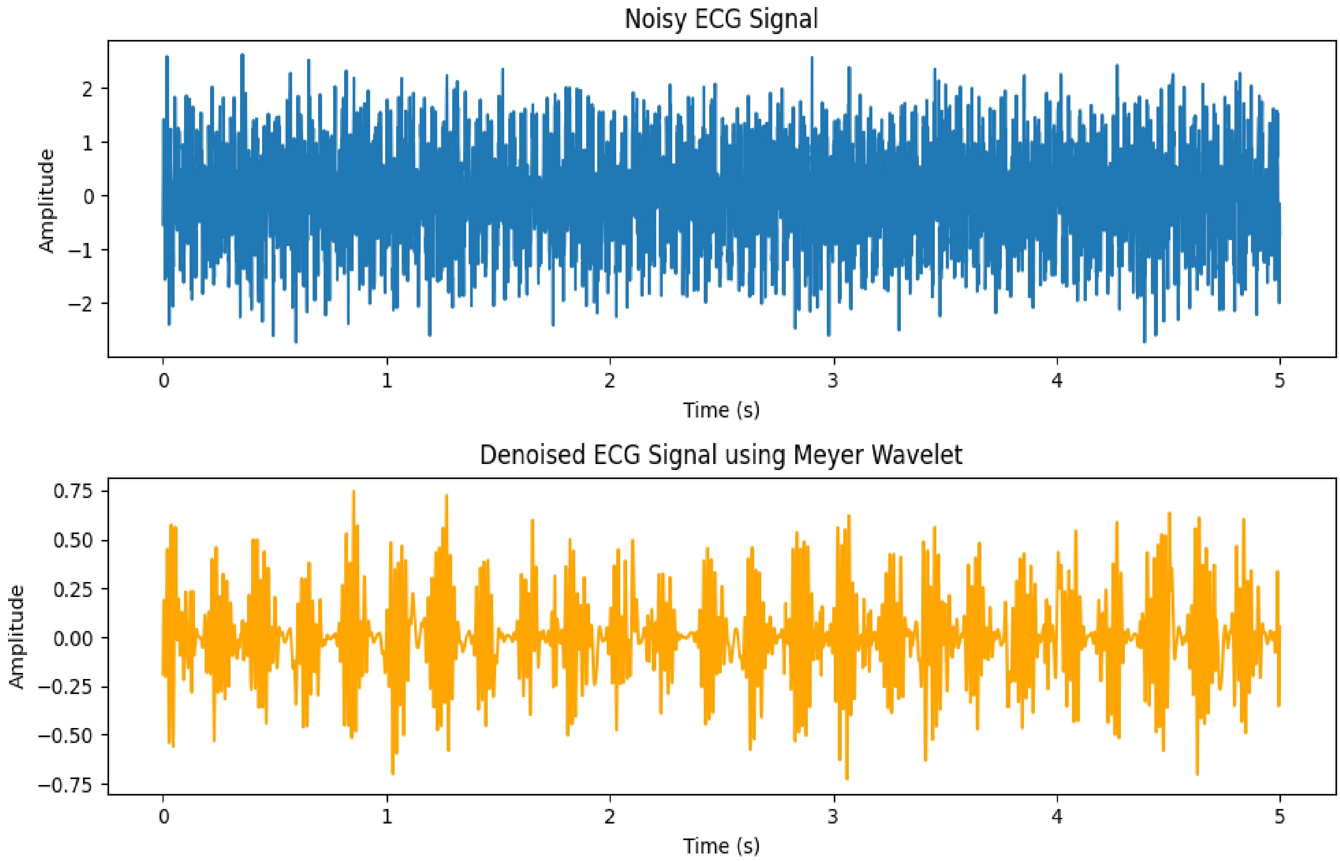

Figure 9. Original and denoised ECG signal using Meyer

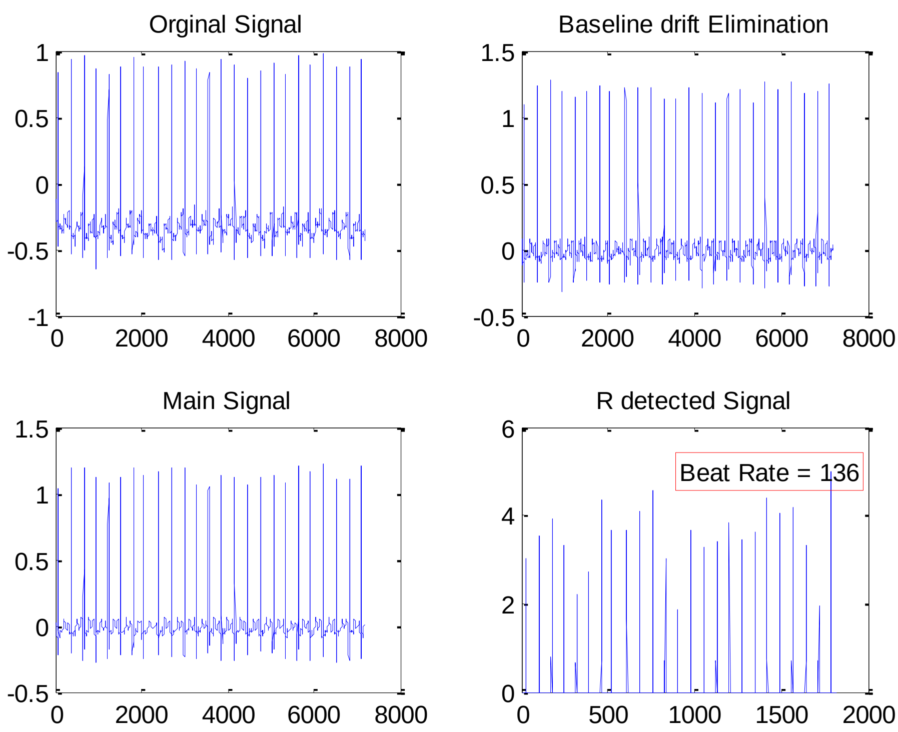

Figure 10. R-peak detected ECG signal using Meyer

Table 1. Signal to Noise Ratio (SNR in dB) comparison for various wavelets

6Level	Db1(Haar)	Coif5	Symmlet	Bior6.8	Meyer
2	1.37E-06	1.42E-06	1.46E-06	1.64E-06	1.68E-06
3	0.41	0.18	0.03	0.39	0.74
4	1.52	0.32	0.12	13.43	16.42
5	7.99	4.69	0.09	15.35	36.42
6	25.45	19.45	28.56	42.39	45.74

Table 2. Comparison of NMSE for different SNR

SNR	NMSE				
	Blind Method	Semi blind Method	Pilot based 1	Pilot based 2	Semi blind pilot-based
0	0.050	0.050	0.050	0.05	0.030
1	0.048	0.046	0.043	0.040	0.021
2	0.045	0.039	0.035	0.030	0.017
3	0.039	0.035	0.030	0.025	0.010
4	0.035	0.030	0.025	0.017	0.008
5	0.026	0.021	0.016	0.012	0.005
6	0.020	0.016	0.013	0.010	0.004
7	0.015	0.010	0.008	0.005	0.003
8	0.010	0.007	0.005	0.003	0.002
9	0.009	0.005	0.004	0.003	0.002
10	0.008	0.004	0.003	0.002	0.001

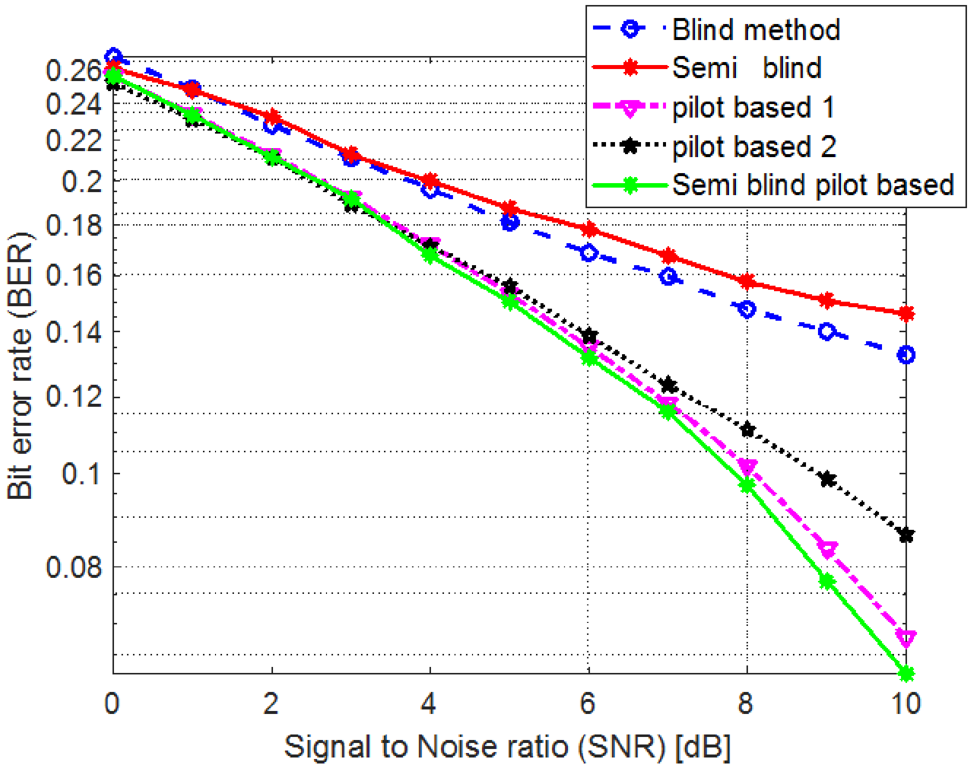

Figure 11. SNR Vs BER for different channel estimation techniques

Table 3. Comparison of the Proposed Wearable Healthcare System with State-of-the-Art Methods in Terms of SNR, BER, and Computational Complexity

Reference	Method	SNR (dB) ↑	BER ↓	Computational Complexity
[22]	AI-Assisted WBAN for Healthcare	28.7	3.1×10^{-5}	$High\ (O(n^2))$
[23]	IoT-Based Smart Healthcare with Edge Computing	26.4	4.8×10^{-5}	$High\ (O(n^2\ log\ n))$
[24]	Energy-Efficient WBAN Communication	24.1	6.3×10^{-5}	$Low\ (O(n))$
[25]	Blockchain-Enabled Remote Healthcare Monitoring	27.5	2.9×10^{-5}	$Very\ High\ (O(n^3))$
[26]	Conventional Telemedicine Systems	22.8	8.7×10^{-5}	$Low\ (O(n))$
This Study	Proposed System (Wearable + 5G Massive MIMO)	32.5	1.2×10^{-5}	$Moderate\ (O(n\ log\ n))$

The spectral characteristics were studied and the signal-to-noise ratio (SNR) was calculated. For the ECG considered in this study, the heart rate is 60 bpm.

From Figure 10, the beat rate obtained using the Meyer wavelet is 136 which is better than biorthogonal and symmlet wavelets and it is found to be suitable for obtaining the accurate beat rate of 74 bpm. The obtained heartbeat rate is within the acceptable range.

Table 1 compiles data from diverse levels, illustrating outcomes acquired through different methods such as Db1 (Haar), Coif5, Symmlet, Bior6.8, and Meyer. Initially, at levels 2 and 3, values remain relatively diminutive, hovering around 10-6 and exhibiting modest decimal figures. However, as the levels ascend to 4, 5, and 6, values undergo a substantial surge, notably evident in methods like Bior6.8 and Meyer, where they escalate to magnitudes within the 10s and 40s, respectively. This pattern suggests an increase in the complexity or intensity of the analyzed phenomena or processes as the levels advance, highlighting the differing effectiveness or impact of the methods employed. Notably, the significant rise in values associated with Meyer implies its superiority over other techniques, emphasizing its potential as the preferred method in this context.

Figure 11 compares the bit error rate (BER) for SNR values ranging from 0 dB to 10 dB. Generally, the BER decreases as SNR increases. As shown in Figure 11, the BER significantly decreases in the semi-blind pilot-based scheme compared to other techniques. Table 2 lists the obtained NMSE values for different channel estimation methods. Based on the data from Figure 11 and Table 2, it is concluded that the semi-blind pilot-based scheme is more suitable for massive MIMO communication.

Table 3 compares the proposed wearable healthcare monitoring system with 5G Massive MIMO against state-of-the-art methods based on Signal-to-Noise Ratio (SNR), Bit Error Rate (BER), and Computational Complexity. The proposed system outperforms existing methods by achieving higher SNR (32.5 dB) and lower BER (1.2×10^{-5}), ensuring improved signal quality and reliable data transmission. Compared to AI and blockchain-based approaches, it maintains moderate computational complexity $(O(n\ log\ n))$, making it more efficient for real-time applications. Traditional telemedicine and IoT-based methods show lower performance due to higher BER and limited signal enhancement capabilities.

The limitation of the study includes:

- The system's performance is constrained in areas with limited 5G coverage, affecting real-time monitoring reliability.
- Wireless transmission of sensitive health data poses risks of cyberattacks and unauthorized access, requiring robust encryption and authentication.
- Continuous data acquisition and transmission increase power consumption, necessitating energy-efficient hardware and optimized protocols.

6. Conclusion

This study presents a wearable computing-based wireless healthcare monitoring system that integrates feature extraction, wavelet-based preprocessing, and 5G-enabled Massive MIMO communication to enhance real-time patient monitoring. The system leverages a wireless sensor network (WSN) to connect multiple patient devices, ensuring efficient data acquisition and transmission. A detailed performance analysis of wavelet-based preprocessing demonstrated that level 5 decomposition optimally enhances Signal-to-Noise Ratio (SNR) without significant gains at higher levels. The Meyer wavelet outperformed the biorthogonal wavelet by 14.7% and had the greatest SNR (45.74 dB) among the wavelets examined, demonstrating its efficacy in spectral feature extraction and ECG signal denoising. The study also emphasizes how semi-blind pilot-based systems outperform traditional methods in lowering Bit Error Rate (BER), hence increasing the dependability of wireless transmission.

7. Practical Advantages

The suggested solution has a number of useful benefits for actual healthcare applications. It lessens the strain on the conventional hospital infrastructure by enabling continuous, real-time vital sign monitoring through the use of wearable computing and 5G technology. Massive MIMO integration increases data transmission efficiency, enabling minimum delays for remote patient monitoring by healthcare practitioners. Furthermore, wavelet-based preprocessing greatly improves the quality of ECG signals, which makes them appropriate for prompt medical treatments and early illness identification. The system is perfect for large-scale deployments in hospitals, senior care facilities, and telemedicine platforms since it can manage several patients at once via WSN communication.

8. Future Research Directions

Future research may build upon this study in several significant domains. Initially, the incorporation of artificial intelligence (AI) and deep learning into the system can facilitate automated anomaly detection and predictive analytics, thereby enhancing patient outcomes. Secondly, the investigation of energy-efficient signal processing methodologies will contribute to the reduction of power consumption in wearable devices, thereby enhancing their sustainability for prolonged utilization. Thirdly, the implementation of rigorous security frameworks, including blockchain-based encryption and federated learning, can significantly enhance data privacy and integrity, thereby ensuring more secure healthcare communications. These advancements will significantly enhance the capabilities of ubiquitous healthcare systems within next-generation smart healthcare ecosystems.

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C. Venkatesan: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing. T. Thamaraimanalan: Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing. D. Balamurugan: Data Curation, Writing - Review & Editing. A. Sivaramakrishnan: Formal analysis, Writing - Original Draft, Writing - Review & Editing. R. Umamaheswari: Formal analysis, Writing - Original Draft, Writing - Review & Editing. M. Ramkumar: Formal analysis, Writing - Original Draft, Writing - Review & Editing. All the authors read and approved the final version of this manuscript.

Funding

The authors declare that no funds, grants or any other support were received during the preparation of this manuscript.

Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Has this article screened for similarity?

Yes

Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

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