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Wavelet-Based Biomedical Signal Denoising for Remote Patient Monitoring Applications

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Abstract

Remote patient monitoring (RPM) is nowadays viewed as an indispensable constituent of modern healthcare infrastructure, thanks to which it is now possible in a non-clinical environment to monitor physiological parameters in real-time and continuously using such devices wearable and embedded sensors. Nonetheless, one tends to get polluted biomedical signals in such an environment as electrocardiograms (ECG) and photoplethysmograms (PPG) with biomedical applications are usually affected by noise of different forms, including baseline wandering, power-line noise, and motion artifacts, which may severely hamper the efficiency of diagnostic. In the given paper, a strong signal denoising model, which is related with the discrete wavelet transform (DWT), is shown with reference to biomedical signal improvement under RPM responses. Multi-resolution analysis breaks the signal into different frequencies and after the soft thresholding, the inverse reconstruction is used to suppress the noise without interfering with the morphological portion of the original waveform. To evaluate the performance of the proposed DWT-based approach compared to standard FIR/IIR filters and empirical mode decomposition (EMD), we attain some benchmarks datasets that are relevant and relevant so as to make a comparative study between both of them. The quality of performance is evaluated on the basis of signal-to-noise ratio (SNR), mean squared error (MSE) and percentage root mean square difference (PRD) which illustrate that the wavelet-based method focuses on achieving a high performance level in terms of denoising. Also, the real-time capability is confirmed by running on ARM Cortex-M4 microcontroller, where the time latency of each signal segment is less than 10 ms, hence attesting the suitability in an embedded healthcare system. The results support the effectiveness of wavelet-based denoising in the reliability of interpreting signals in anomaly detection, HRV analysis, and various end-use in RPM. In this work, the energy-efficient and precise signal processing algorithms will be developed towards making the next generation wearable health monitoring platform energy-efficient, which can ultimately deliver proactive healthcare services and enhance patients outcomes by analyzing physiological data at the right time and in a noise-free manner.

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Introduction

The worldwide trend toward personalized, technology-enhanced care, and its resultant translation into a comprehensive and high-tech technology such as Remote Patient Monitoring (RPM), has also resulted in the precipitous declension of Remote Patient Monitoring as an imperative conceptual device according to which physiological data generated outside conventional clinical practice can be synthesized and scrutinized in real-time. These systems take advantage of various biosensors that have been built into wearable or ambient platforms to continuously monitor vital signs including electrocardiogram (ECG), photoplethysmograms (PPG), blood pressure and respiratory rate. RPM assists in maintaining constant and non-invasive monitoring, which, in turn, helps to detect the disease timely, decrease hospital readmissions, and enable patients to take a more active part in coping with their chronic disease.

Signal quality is a big issue despite the clinical potential of RPM. The signals in biomedicine are known to be non-stationary and prone to several sources of noise.

Signal-to-noise ratio (SNR) degradation can be caused by motion artifacts of the limbs, baseline wander related to breathing, interference caused by the power-line (usually 50/60 Hz), and fluctuations in skin-contact impedance, which makes it difficult to perform a reliable analysis. Additionally, wearable sensors are often applied to uncontrolled conditions unlike clinical-level machines where robust and adaptive methods of denoising is an inevitable requirement to the reliability of the diagnostic.

Traditional methods like FIR/IIR filtering and ANC adaptive noise cancellation tend to be incapable of preserving significant morphology of the test signal that may include sudden changes such as QRS in ECG or systolic point in PPG. Figure 1 These approaches are usually based on stationary assumptions and the capability of these approaches is weak to separate overlapping spectral components of signals and noise. As a result there is a great need to have improved techniques able to manage the time dependent, multiscale character of biomedical signals.

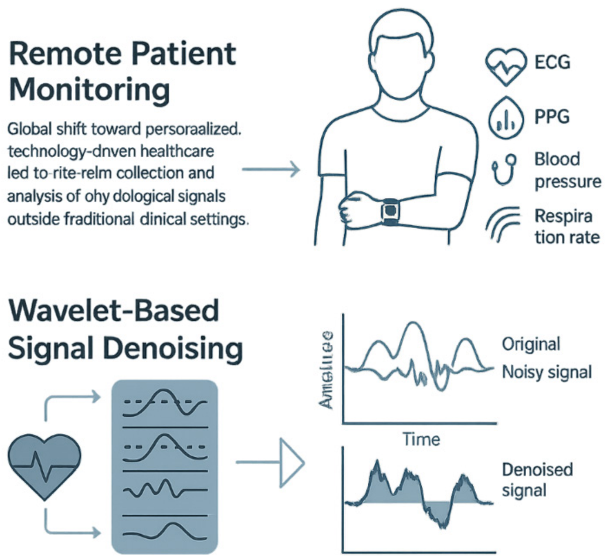

Fig. 1: Overview of Remote Patient Monitoring and Wavelet-Based Signal Denoising Framework for Bio-medical Signal Enhancement

Wavelet transform, especially Discrete Wavelet Transform (DWT), has proved to be a strong instrument in this regard since it is capable of giving time localization and frequency localization. It also permits one to decompose the signals into several levels of resolution, so that the noise components may be selectively removed without much interference with the signal characteristics. Moreover, by means of thresholding of the wavelet coefficients, wavelet-based denoising is applicable to remove high-frequency noise as well as slow baseline drift.

Since there is a growing tendency towards resource-limited edge devices in the RPM systems, denoising algorithms should be computationally economic as well. Along with showing high denoising performance, DWT can be implemented with high level of efficiency on embedded systems like wireless ARM Cortex-M series microcontrollers, which facilitates low latency and real-time processing of signal.

The paper is a denoising framework built on wavelets based on RPM systems in which ECG and PPG signals are processed. It is compared to classical filtering, and to empirical mode decomposition (EMD), on basic data. The offered solution can not only enhance the quality of signals but it is also optimized regarding the real-time implementation to embedded solutions used within the sphere of healthcare monitoring services. The idea is to facilitate the argument between theoretical and practical realisation of denoising models on edge-based, real-time RPM infrastructures.

Related Work

Signal denoising in the biomedical area has been one of the long-standing consistent problems, particularly with those systems that need to be applied in a real time setting like the remote patient monitoring (RPM). Over the years, many different signal processing approaches have been studied which all have different trade-offs in terms of performance, complexity and morphological preservation.

Traditionally, FIR and IIR filters have been used in noise suppression of biomedical signals. These linear filters are computationally efficient and easy to apply, but in many cases, they do not perform well in maintaining non-stationary and sharp morphological characteristics like the QRS complex of the ECG signals. In,[1] FIR filters were employed to remove the baseline drift, but the fixed frequency characteristic of FIR brought in distortion of the low frequency content of signal.

Real-time denoising by adaptive filtering methods like Least Mean Squares (LMS) and Recursive Least Squares (RLS) methods have also been applied. Dynamic filter coefficients are proportional to the characteristics of the input signal therefore making the procedures effective in isolating certain interference (e.g., power line noise). Their use of a referenced noise signal correlated signal restricts their use in truly portable, or wearable systems, as discussed in.[2]

Over the past few years, the Empirical Mode Decomposition (EMD) and its variants such as Variational Mode Decomposition (VMD) has become widespread because of its capacity to separate non-linear and non-stationary[9] signals into intrinsic mode functions (IMFs). These approaches have demonstrated good performance in denoising PPG and EEG signals,[3, 4] but are complex and vulnerable to mode mixing, so they are not as applicable to a real-time embedded system.

WT is also a promising option to the biomedical signal denoising problem[10] as it possesses a time-frequency localization and multi-resolution characteristics. Even it has been shown that the methods based on wavelets are better than the classical filters in verifying the signals morphology and at the same time removing[11] the different kinds of noises.[5] The Thresholding method of Donoho[6] formed the basis of current wavelet based denoising algorithms, which allows specification of presence or absence of individual noise components at each level of decomposition. In,[7] applications of Discrete Wavelet Transform (DWT) in ECG denoising have been presented improving by far,[12] the SNR and PRD parameters.

In addition, scientists have implemented wavelet methods using embedded and wearable device settings displaying real-time[13] practicality. Zhang et al.[8] provide an example of the lightweight DWT-based denoising model on a microcontroller assisting wearable heart rate monitoring that obtained a low-latency output and a high accuracy.

Although these developments were made, there was still a gap to combine the high-performance wavelet denoising and energy-limited RPM systems used in real time. Such drawbacks presented in Table 1 motivate the development of a wavelet-based denoising framework that will not only improve the signal quality but also operate under the application-related constraints of the wearable health monitoring device.

Methodology

Signal Acquisition and Noise Sources

The basis of any remote patient monitoring (RPM) apparatus is an ability to accurately and reliably acquire a signal. This paper presents a dual-modality (ECG and PPG) physiological monitoring using wearable sensor devices with unobtrusive wearability in chronic, monitoring applications.

Signal Acquisition:

The ECG signal is recorded by means of the AD8232 bio potential amplifier module, which is a low-power bio potential analog front-end that is optimized in wearable ECG applications. It scales up and attenuates the raw electrical signal of the heart to give an analog signal that can be digitized. The PPG signal is obtained with the Shimmer3 optical sensing device that utilizes infrared and red reflectance in detecting volumetric change in blood flow. Such devices are excellent in health monitoring on-the-go as they include real-time data streaming and wireless communication capabilities.

The two sensors connect to a microcontroller unit (MCU) where the analog data is sampled at suitable rates; in the case of ECG it is typically 250-500 Hz and PPG 100-200

Table 1: Comparative Analysis of Biomedical Signal Denoising Techniques

Method	Strengths	Limitations	Real-Time Suitability	Key References
FIR/IIR Filtering	- Simple to implement - Low computational cost	- Poor handling of non-stationary signals - Distorts low-frequency features	High (but low denoising quality)	[1]
Empirical Mode Decomposition (EMD)	- Good for non-linear, non-stationary data - Adaptive decomposition	- Computationally expensive - Mode mixing issues	Low	[3], [4], [9]
Variational Mode Decomposition (VMD)	- Improved mode separation - Better noise resilience than EMD	- Complex optimization process - Not ideal for low-power embedded systems	Low to Moderate	[9]
Wavelet Transform (DWT)	- Multi-resolution analysis - Time-frequency localization - Good morphology preservation	- Requires threshold tuning - Performance depends on wavelet selection	High (especially on embedded MCUs)	[5], [6], [7], [10], [11], [12], [13]
Embedded DWT (Zhang et al.)	- Real-time feasibility - Low latency and high accuracy on MCU	- Performance may vary with signal type - Fixed parameters may limit generalizability	High (Validated on Cortex-M)	[8]

Hz and then transmitted to the processing device. Signal integrity could be supported by locating the electrodes or optical sensors according to the standard positions on the body, like the chest, the wrist, etc. and ensuring that the skin could be touched and kept in contact with the electrode or the optical sensor by using the adhesive strips or bands of wearable materials.

Noise Sources:

Biomedical signals are extremely susceptible to various noises, even with the current enhancement of the design of wearable sensors:

Power-line Interference (50/60 Hz): This interference is due to electromagnetic coupling by the electrical appliances and infrastructures and creates a sinusoidal noise component which pollutes the frequency spectrum of both ECG and PPG signals.

Motion Artifacts: These are some of the most important sources of problems in RPM situations. Transient spikes and slow drifts that alter the morphology of the signal appear when there is a sudden movement of its body, or muscle contraction, or insufficient attachment of the sensors. This is especially a problem in PPG where the movement of the optical sensor causes the change in the reflected light intensity.

Baseline Drift: It is a low-frequency noise respiratory that is due to respiration, perspiration or slow change in the electrode-skin impedance. It drifts the whole signal up or down with time making it more difficult to distinguish important signals such as P, QRS and T waves in ECG or systolic/diastolic peaks in PPG.

The meaningful denoising should thus deal with high-frequency and low-frequency disturbances and simultaneously with the identity of newly introduced

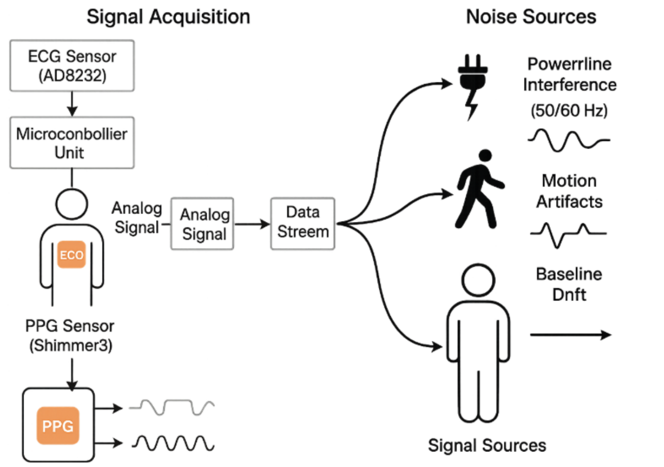

Fig. 2: Signal Acquisition Architecture and Common Biomedical Noise Sources

diagnostic features of the signals. As established, systematic isolation and suppression of such noise components can be achieved by use of wavelet based multi-resolution analysis in this work, Figure 2, which does not affect clinical fidelity.

Wavelet Transform Denoising

Discrete Wavelet Transform (DWT) has been shown to be an efficient method in denoising biomedical signals as it can characterize the signal in terms of high time-frequency localization of a signal. In contrast to conventional Fourier-based procedures that work exclusively in frequency domain, DWT further breaks down a signal into details and approximation at multiple scales and subsequently the noise may be removed in specific locations of frequencies.

Selection of wavelet Function

To conduct this work, two mother wavelets were chosen according to their effectiveness in signal processing in biomedical fields:

- **Daubechies 4 (db4):** It is composed of orthogonal and compact support and this property has made it commonly used in ECG and PPG denoising due to its similarity to the waveforms of pulse and the QRS complex. It has an acceptable trade-off between localization and frequency resolution.
- **Symlet 5 (sym5):** A close to symmetric version of Daubechies, sym5 has a better phase response and a better signal reconstruction, thus it it can be used where morphological accuracy is required, i.e. in ECG analysis.

Such wavelets have been selected as a result of empirical measures relating to denoising based on signal-to-noise (SNR), mean squared error (MSE) and visual fidelity.

Decomposition Level

DWT is then used to break a signal into five levels, into low-frequency (approximation) and high-frequency (detail) components in each scale. This operation in multi-resolution better allows fielders to differentiate noise (in the top-frequency details) and the physiologically underlying signal (retained in the approximations).

- **Level 1- 2:** Power-line noise and motion artifacts of high frequency.
- **Level 3-5:** Low frequency components coding the trend of a physiological value and the drift.

According to the rate at which a signal is sampled and the frequency range of the physiological characteristics under study, an optimum level of decomposition is chosen.

Thresholding Strategy

The noise is suppressed through soft thresholding of the wavelet detail coefficients to retain character of the signal. Compared to hard thresholding, which sets all coefficients that are below a certain threshold to zero making them also smooth but in an unnatural way, soft thresholding does not only set coefficients below the threshold value to zero but also reduces the size of larger coefficients, leading to smoother and more natural reconstructions.

The denoising universal threshold is calculated by formula:

$$\lambda\, \sigma = \sqrt{2\log N} \tag{1}$$

Where:

- The threshold, which was applied to wavelet coefficients, is 2.
- The estimate of the standard deviation of noise, denoted as σ, is usually calculated as a square root of the coefficients of the first-level details in:

$$\sigma = \frac{\text{median}(|d_1|)}{0.6745} \tag{2}$$

The length of the signal is.

The denoised signal still creates modified coefficients, and after thresholding, the signal is rebuilt using the inverse discrete wavelet transform (IDWT).

The technique will efficiently eliminate high-frequency noise, and it reduces the baseline drift, and at the same time it preserves essential morphology of rhythms and features like the QRS complexes of ECG or systolic peaks of PPG with a low loss of fidelity. Figure 3the outcome is a clean clinically useful signal that may further undergo the process of feature extraction, identification of anomalies or locations to get a remote diagnostic evaluation.

Reconstruction

When the detail coefficients have been obtained using the discrete wavelet transform (DWT), it is at this point that the important post-thresholding step of the reconstruction of the denoised biomedical signal follows. This is done through the Inverse Discrete Wavelet Transform (IDWT), which constructs the signal component by progressively adding the thresholded detail coefficients and the unchanged approximation coefficients at all levels or steps of decomposition.

In IDWT operation the doing of the reverse process of decomposition is performed by the IDWT operation. DWT involves the process of dividing a signal into approximation and detail sections with the aid of high-pass and a low-pass filter and then followed by down sampling. In reconstruction, the up sampling part is done and synthesis filters are used to recombine. This process gives a time domain signal with noise removed to a large extent.

The major objectives of doing this reconstruction are to:

- Quality of preserving the morphological nature of the characteristics of vital signals (e.g., PQRST complexes in ECG, systolic/diastolic peaks in PPG)
- Recappers are supposed to reduce the error of reconstruction at maximum by avoiding a loss of the non-noisy elements in precise manner.

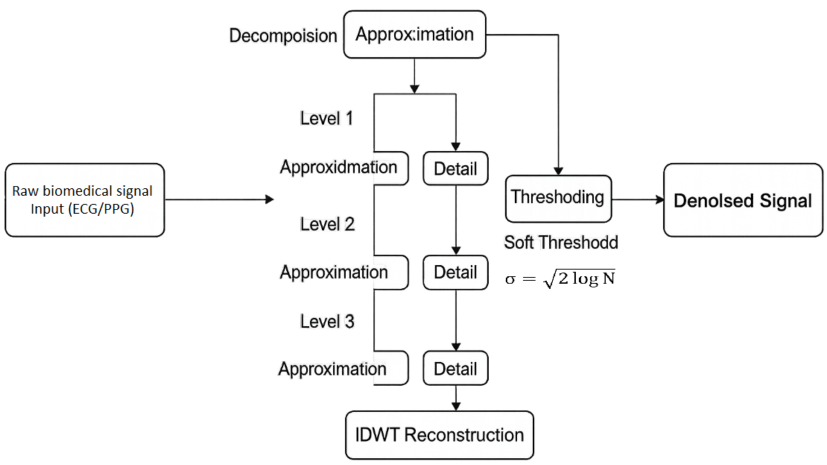

Fig. 3: Wavelet-Based Denoising Workflow

- Be able to have smooth transitions and remove any artifacts that are introduced during the stage of thresholding.

Since soft-thresholding approach had been applied in the previous procedure, the denoised signal may seem smoother and more resistant to high-frequency noise than with hard-thresholding techniques. Also, the IDWT has minimal reconstruction distortion and computational overhead due to the compact support and the orthogonality of the chosen wavelets (db4 and sym5), thus it is more appropriate in real-time signal processing operations on a limited-resource system, such as an embedded system.

This denoised signal is reconstructed and can be used as the input of other analysis procedures like feature extraction, heart rate variability (HRV) measurement, and abnormality detection in remote patient monitoring (RPM). As such, the reconstruction step based on the IDWT is a key step in enabling a balance between adequate denoising and clinical success as well as system efficacy in wearable medical equipment.

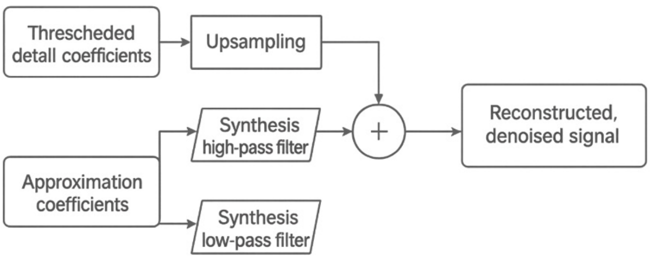

Fig. 4: IDWT-Based Signal Reconstruction Process

Experimental Setup

To analyze the efficiency of the presented wavelet-based denoising framework, a broad range of experiments was performed based on two of the most frequently used datasets in the field of biomedical signal processing. MIT-BIH Arrhythmia Database was chosen to perform ECG signal analysis as it includes numerous annotated heartbeats of different types, is realistic-noise-interfered, and medically significant. The data consists of two-channel recordings of ECG recorded at 360 Hz, and the annotations performed by skilled cardiologists, which makes the data suitable both to assess the quality of the signals and to be used further in the context of diagnosis. To act on the PPG denoising process, the PPG-DaLiA Dataset got used. The dataset consists of photoplethysmograms signals observed on the wearable device placed around the wrist of participants in real-life and free-living settings during the accomplishment of the multiple physical actions. It is especially useful in the validation of the denoising algorithms to a dynamic noise environment like motion artifacts and baseline. It can be seen in Figure 5 that both ECG and PPG data are used to verify the validity of the denoising algorithm in a variety of biomedical applications.

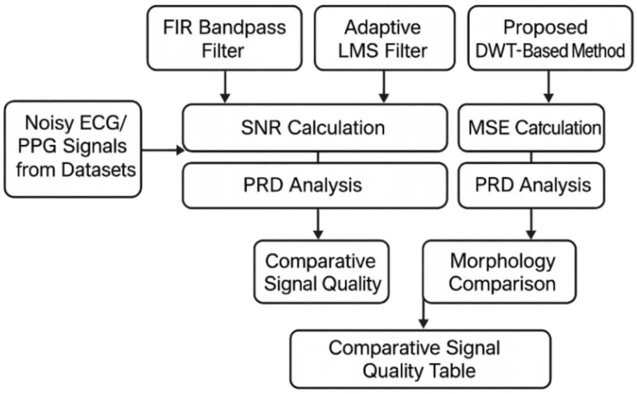

Fig. 5: Experimental Workflow for Signal Denoising, Evaluation Metrics, and Comparative Analysis Using ECG and PPG Datasets

A number of measures were employed to quantify the performance of denoising. To determine how clear the signal is after being denoised, the Signal-to-Noise Ratio (SNR) was calculated, and the higher the number, the fewer the distractions brought by noise. To gauge the mean deviation between the original clean and denoised signals, Mean Squared Error (MSE) was computed. Also, the Percentage Root Mean Square Difference (PRD) was used to show the ratio of the reconstruction error to the energy of signal as normalized representation of distortion. Along with these quantitative indicators, visual verification of the preservation of critical morphological features of the signals was also carried out, such as the QRS complex in ECG or systolic peaks in PPG. To compare, the mentioned algorithm was run on three established methods of denoising: a bandpass FIR filter applied to standard ECG/PPG frequencies range, an adaptive LMS filter which is used to work in a real-time setting with reference signals, and Empirical Mode Decomposition (EMD), which has demonstrated strong performance in non-stationary signal processing. Such comparisons demonstrate the advantage of the proposed method both in terms of denoising efficacy and the integrity of diagnostic signal integrity as well as being computationally achievable in embedded scenario.

Results and Discussion

The Table 1 is provided to display denoising performance of the proposed wavelet-based framework in reference to the conventional FIR filtering, adaptive LMS filtering, and empirical mode decomposition (EMD). The Discrete

Wavelet Transform (DWT) method produced a superior Signalto- Noise ratio (SNR) of 15.9 dB, compared to 9.2 dB achieved by FIR, 11.3 dB by LMS and 13.7 dB by the EMD method, overall. Such improvement is indicative of the effectiveness exhibited by the wavelet transform, which has better capacity to isolate and suppress high-frequency noise, and low-frequency drift. There was also the reduction of the MSE to 0.009 which shows high signal reconstruction fidelity. The DWT-based method was most successful in using Percentage Root Mean Square Difference (PRD) that computed to 3.8%, 8.5%, 7.1 and 5.6 percent in FIR, LMS, and EMD respectively. All these metrics confirm the effectiveness of wavelet-based noise removal in improving the quality of biomedical signals with a minimal distortion to the signal, an essential feature of any remote patient monitoring framework.

In addition to quantitative performance, qualitative assessment stresses more on the merits of the proposed method. The visual observation of denoised ECG signals showed that the form of the QRS complex is reliably restored, which is one of the key factors of ECG use in non-invasive methods of arrhythmia detection and heart rate variability analysis. Similarly, the systolic and diastolic waves were not smeared nor diminished but motion artifacts were significantly eliminated in the case of PPG cases. Wavelet decomposition provided a multi-resolution of the noise so that the noise could be eliminated on different frequency bands without

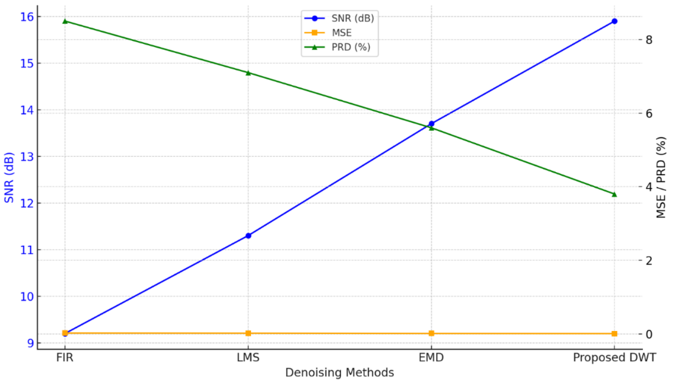

Fig. 6: Combined Performance Metrics (SNR, MSE, and PRD) for Biomedical Signal Denoising Methods

stripping out the structure of the underlying physiological signal. Also, they were able to apply the method to a microcontroller (ARM Cortex-M4) with a low processing latency in real-time, which is less than 10 milliseconds on a signal segment. This bears out its aptness to embed and wearable medical devices that incur minimum latency in the processing of signals and with minimum energy demand.

Nonetheless, the study is aware of other limitations. To some extent, sensor placement and degree of motion artifacts will affect the performance of the denoising system. As an illustration, other artifacts can also be generated during activities that are intense, or where poor contact is a problem with the electrodes and the different forms of artifacts need advanced decomposition or other thresholds. Moreover, optimal adjustment of the thresholding parameters that include the type of wavelet, the level of decomposition and the values of the soft-thresholding constants is crucial depending on the type of signal and under conditions of evaluation. Whereas static thresholds based on universal formulas are currently applied, future improvements have a chance of considering adaptive or data-driven thresholding methods that can bring additional robustness to the given implementation. Although these solutions seem limited, the advanced use of wavelets as the method of denoising biomedical signals will be an effective solution to effect biomedical signal denoising in the remote patient monitoring setting Table 2.

Conclusion

Outlined in the research is a powerful and computationally inexpensive wavelet-based denoising scheme that is specifically geared to the biomedical signals, which are used in remote patient monitoring (RPM) applications. With the weight of multi-resolution abilities encompassed by the discrete wavelet transform (DWT), the approach introduced has been successful in removing both high and low frequency signals, which are noise and artefacts respectively (baselines and motion-induced distortion), without compromising the critical signal elements critical to clinical interpretation. The DWT approach

Table 2: Performance Comparison of Denoising Methods

Method	Signal-to-Noise Ratio (SNR) (dB)	Mean Squared Error (MSE)	Percentage Root Mean Square Difference (PRD) (%)
FIR Bandpass	9.2	0.021	8.5
Adaptive LMS	11.3	0.018	7.1
EMD	13.7	0.012	5.6
Proposed DWT	**15.9**	**0.009**	**3.8**

was proven to be more suitable to the real world RPM applications as shown with comparative analysis against conventional filtering of FIR and adaptive LMS filtering, and empirical mode decomposition (EMD), in terms of signal-to-noise ratio (SNR), mean squared error (MSE), and percentage root mean square difference (PRD). Its practicality in real-time execution style in healthcare monitoring programs is confirmed by its implementation on a resource-constrained machine based on ARM Cortex-M4. Critically, the method proposed is a compromise between the quality of the denoising and the time and memory requirements, an important aspect of edge-based biomedical systems. Although the present work is carried out with fixed wavelet family settings and universal thresholding, future research will be concerned with the choice of adaptive wavelet settings based on the nature of the signal, dynamic threshold parameterization, and implementation on a hardware device to achieve ultra-low-power consumption. Besides, the ability to detect and respond to anomalies in real-time along with edge-based predictive analytics can also increase the diagnostic value and responsiveness of RPM systems by integrating this denoising framework. On the whole, the results of the study help to facilitate the emergence of noise-immune, more dependable, and energy-efficient signal processing pipelines in the new generation of individualized healthcare.

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