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Electrocardiogram signal processing algorithm on microcontroller using wavelet transform method

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ABSTRACT

The electrocardiogram (ECG) is an important parameter for analyzing the cardiac system. It serves as the primary diagnostic tool for patients with suspected heart disease, guiding appropriate cardiac investigations according to the disease or condition suspected. However, ECG measurements may generate noise, leading to false diagnoses. The wavelet transform is an effective and widely-used technique for eliminating noise. Typically, analysis and generation algorithms are developed on computer and using software built in. This paper presents a noise elimination algorithm based on the wavelet transform method, designed to operate on resource-limited Node microcontroller unit (MCU). An efficiency study was conducted to determine the optimum mother wavelet implementation of the algorithm, and the results showed that, when considering synthetic ECG signals, db4 was the most suitable for eliminating interference by achieving the highest signal to noise ratio (SNR) and correlation coefficient. In addition, this algorithm prototype can analyze ECG signals using the wavelet transform method processed in a microcontroller and is accurate compared to reliable programs. It has the potential to be further developed into a low-cost portable ECG signal measurement tool for use in remote medicine, healthcare facilities in resource-limited areas, education and training, as well as home monitoring for chronic patients.

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1. INTRODUCTION

Medical professionals and patients may be shielded from coronavirus disease starting in 2019 (COVID-19) exposure by telemedicine and eHealth platforms, which use high-speed communications networks and application software for the delivery, management, and monitoring of medical services [1]. It is evident that eHealth and telemedicine systems are crucial for addressing COVID-19 on a worldwide scale [2]. As the disease spreads around the globe, medical facilities utilize telemedicine and eHealth platforms in a variety of ways to improve patient care [3]. These include decreased medical expenses, diminished worker tiredness, more worker sustainability, diminished physician exposure, and diminished need of personal protective equipment (PPE) suits, such as dust filter masks and respirators [4].

In addition to the remote medical software platform, there are algorithms embedded in the remote medical system. An algorithm that makes it easier to administer patient summaries that have been analyzed by remote analytics [5], [6]. In order to deliver the most recent information, artificial intelligence (AI) chatbot is used. Regarding COVID-19, it offers prevention recommendations as well as potential societal remedies. It also provides real-time situation reports to medical practitioners [5]. A COVID-19 screening tool is now being developed using AI to offer preliminary testing for patients with symptoms. and, if required, suggest additional medical care. However, when there is sufficient and reliable data, both application software platforms and AI chatbots will become more valuable and significant. As a result, a lot of research has been done on developing mobile medical devices that include internet of things (IoT) technologies. Patients can independently measure the fundamental variables required for diagnosis and transmission to medical staff.

One of the most crucial physiological measures is pulse. The term "pulse" describes the pressure produced as blood vessels expand and same in time with the heart's rhythmic contraction and expansion. Therefore, the blood flow wave in the aorta that causes an aneurysm is caused by pulse rate [6]. Thus, heart rate can be determined using pulse physiological parameters [7]. The study [6] presented an autonomous bed shifting system for long-term bedridden patients using the patient's pulse rate as a measure of discomfort.

Disease monitoring is necessary because some medical problems necessitate long-term patient care, especially in the case of chronic diseases [8]. Therefore, it is crucial to continuously check for such occurrences. The monitoring of blood sugar levels, for instance, will vary depending on the individual. This aids in scheduling activities, medications, and meals [9]. The architecture system was created using sensing technology. The technology attempts to deliver real-time information on glucose levels and body temperature. This also contains other data such as environmental temperature. This information is presented graphically and is easily legible by humans for end users such as patients and healthcare professionals. A remote monitoring system for individuals with persistent metabolic problems is described in the paper [8]. These include blood pressure and glucose monitors, smart scales, pulse oximeters, activity trackers, and blood pressure monitors. The device is also capable of performing analyses that will help with medical diagnostics.

Tele-ECG is a new IoT-based electrocardiogram (ECG) monitoring device that enables remote medical monitoring of the condition of the heart [10]. The systems are still inferior to instruments used by experts. However, by monitoring the patient's ECG over time, the procedure offers basic surveillance. The ECG, which displays the heart's recorded electrical activity via electrodes on the body's surface, is thought to be one of the most recognizable representations of heart function [10]. Heart electrical activity and heart rate fluctuations are measured by physiological parameters ECG [11].

Applications for IoT and health surveillance are presented in the research [12]. Through sensors and portable devices, the system is intended to capture ECG data together with other healthcare data. The author also discusses on safely uploading these data to the cloud. This enables immediate access to medical specialists. Given that earlier systems were expensive and had huge mounting locations, some researchers [11] have suggested a 12-lead ECG system. Because of this, the suggested solution is portable and has produced successful outcomes for home isolate systems. Additionally, ECG data can be sent from a distant area to any point in the world to a medical specialist. Neyja *et al.* [13] proposed low-cost ECG health monitoring system using internet of things with automated analytics and alarms includes energy-efficient wearable sensor devices. The systems are linked to a smart gateway that can be accessed by cardiovascular caregivers.

To monitor patients' ECG signals using a mobile tele-ECG application and do health assessments without a doctor's involvement, was developed by Choudhari *et al.* [10]. The hidden Markov model (HMM) and ECG sensors-based healthcare system implementation proposal was proposed by Nurdin *et al.* [14] with the intention of enhancing patient monitoring and immediate patient assistance in case patients with diseases related to the cardiovascular system. The construction of an ECG monitoring system was then described by Rizqyawan *et al.* [15], in which the user can use the system while ECG signals are being transmitted. Finally, D'Aloia *et al.* [16] suggested that the design, execution, and development of ECG follow-up research.

According to research articles [10]–[16], it is a remote medical system that transmits ECG signals obtained from sensors and transmitted via the Internet to medical personnel via the internet of things. These studies, however, only send the raw sensor data collected from them without filtering the ECG signal, which can result in inaccuracies in the ECG. The medical professionals will diagnose patients incorrectly if they receive muddled signals because of noise. Only study [12], [14] suggested a technique to measure R-R peaks to calculate heart rate, and the algorithm may be prone to errors if the ECG data contains noise.

The measured ECG readings are contaminated by noise. ECG noise can take many different forms, including: *Random noise* called as gaussian noise occurs during transmission, *Muscular artifacts* or noise caused by muscle contractions (MA). *Electrode motion* interference caused by the movement of the body, which moves the electrode and amplifies the signal. The chest region moves equally as a result of breathing, creating baseline wander (BW) noise [17]. The ECG activity data is obscured by all four noises, which can also lead to incorrect heart rate estimations and difficult R peak detection.

In paper [18] discusses the results of using different types of wavelet filters with various thresholds and levels to de-noise ECG signals. The study concludes that the wavelet filter is a good choice for de-noising ECG signals due to its ability to suit many signals and applications. However, it is crucial to choose the appropriate wavelet filter type that is similar to the signal in shape or close to its shape. The study finds that the four-level Daubechies (db4) type is optimal for the Massachusetts institute of technology-Beth Israel arrhythmia (MIT-BIH) database, while the level two of Symlets 4 (sym4) is suitable for ECG signals from the monitoring system. The discrete wavelet transform (DWT) based wavelet denoising technique is used with three different wavelet functions and four different thresholding methods [19]. The study involved the analysis of ECG signals collected from a cohort of ten female participants aged between 20 and 25 years. These signals were obtained while employing the Stroop color-word test as a means of inducing mental stress. The result shows that the Coiflets 5 (coif5) wavelet function and the and rigrsure thresholding rule are the most effective for removing noise from ECG signals, as demonstrated.

Within the scope of study [20], an innovative approach is introduced for the purpose of reducing noise in ECG signals through the utilization of wavelets. The methodology centers around the application of a genetic algorithm, which systematically explores an extensive array of quadrature filter banks. Its objective is to identify the optimal filter bank that results in the minimal signal-to-noise ratio (SNR). Consequently, the wavelet and scaling functions associated with the selected filters are acknowledged as the most effective choice for achieving the task of de-noising. Simulation results show that using the proposed method and the obtained wavelet improves the SNR of the noisy ECG signal by about 2.5 dB. While Majumdar [21] describes a proposed method for de-noising ECG signals using wavelet energy and a sub-band smoothing filter. In contrast to the conventional approach of wavelet threshold de-noising, this novel method exclusively targets wavelet coefficients necessitating threshold de-noising, determined through wavelet energy analysis. Meanwhile, it retains the original values of other coefficients. Furthermore, the technique incorporates a sub-band smoothing filter to amplify the ECG signal's quality through advanced noise reduction. The experimental results show that the proposed method effectively removes noise from the noisy ECG signals compared to existing methods.

In recent years, advancements in medical research have led to significant breakthroughs in the field of cardiac health and diagnostics. One notable area of progress has been the development of innovative techniques for analyzing ECG signals, aiming to detect critical features like the QRS complex and R-peaks with remarkable accuracy and efficiency. Research such as study [22] highlights the integration of chaos analysis, short-time Fourier transform (STFT), and principal component analysis (PCA) to automate QRS complex detection, offering impressive sensitivity and accuracy rates. In a similar vein, Gupta *et al.* [23] introduces a novel application of PCA for R-peak detection, avoiding the need for pre-processing in noisy ECG signals. Meanwhile, Gupta *et al.* [24] presents a computer-aided diagnosis system utilizing chaos analysis to extract non-linear patterns in ECG signals, enhancing arrhythmia detection. Beyond ECG analysis, other studies such as studies [25] and [26] apply machine learning techniques to retinal blood vessel segmentation and the identification of high-risk carotid artery plaques, demonstrating the potential for automated disease detection and prevention. Additionally, research like [27] explores the importance of collateral circulation in preserving myocardium during coronary artery occlusion, emphasizing the need for accurate collateral flow assessment in surgical planning. Furthermore, Li *et al.* [28] introduces a motion compensation method for 3D coronary artery reconstruction, which proves effective in reducing artifacts and improving image quality. Finally, Velut *et al.* [29] analyzes coronary trees using magnetic resonance angiography (MRA) to estimate the capability of MRA in providing insights into the vascular network. This collective body of research represents a significant leap forward in the diagnosis and treatment of cardiovascular and arterial conditions, promising enhanced accuracy, automation, and patient care in the field of cardiac health.

The utilization of wavelet transform, an advanced and effective technique for noise reduction, has gained prominence in enhancing the performance of ECG signal processing algorithms, as demonstrated in previous studies [18]-[29]. However, it is noteworthy that, up to this point, wavelet transform-based signal processing has primarily been confined to traditional computer-based processing platforms and software applications like MATLAB and LabVIEW. One notable gap in the existing research landscape is the limited exploration of implementing wavelet transform algorithms for ECG signal processing within embedded systems, specifically microcontrollers. To date, there has been a dearth of investigations into the adaptation of wavelet transform techniques to microcontroller-based ECG signal processing. This represents an uncharted territory in which the potential benefits of wavelet transform, known for its efficacy in noise reduction, have yet to be fully realized. Therefore, this research endeavors to bridge this gap by presenting a novel approach: the application of wavelet transforms principles for ECG signal processing on a microcontroller, specifically the node MCU. This pioneering effort seeks to unlock the advantages of wavelet transform in noise elimination within the context of resource-constrained embedded systems, potentially extending its utility to a broader range of real-world applications.

2. ECG SIGNAL PROCESSING PROCESS

There is noise in the measured ECG data. A data processing step is required to get rid of the noise and get a clear signal. Signal processing entails two steps: Wideband noise removal and baseline wandering noise removal both employ the wavelet transform approach. Wavelet transform: wavelet transform is a commonly used method for signal estimation [30], [31] and signal compression [32]. Since the Fourier transform simply analyzes the signal in terms of frequency, the wavelet transform transforms the signal to be considered in terms of position and frequency [30]. So, the wavelet transforms signal exhibits less distortion as a result. The ECG signal is also a type of non-stationary signal since it represents the electrical activity of the heart during each heartbeat, which changes over time [33]. A Fourier transform that is appropriate for the analysis of discrete signals is therefore inappropriate. The wavelet transform's foundation is the extraction of the signal's edge components so that each sub-characteristics components can be considered [31]. Definition of wavelet transformation in mathematics constant is

$$W(a,b) = \int_{-\infty}^{\infty} f(t)\psi_{a,b}(t)dt \tag{1}$$

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi^*\left(\frac{t-b}{a}\right) \tag{2}$$

When $f(t)$ is signal, $\psi_{a,b}(t)$ is an analytical function with a time shift, scalability feature. In practice, we can use the discreate wavelet transform to calculate the coefficients for each order of subcomponents (decomposition). The decomposition can use a set of finite impulse response (FIR) filters that act as low pass filters and high pass filters. Then, reduce the sample frequency in half (down sampling). It is possible to employ the discrete wavelet transform algebraically; the fundamental convolution procedures are given

$$a_n^{(i)} = \sum_{k=0}^{N-1} g_k a_{2n-k}^{(i-1)} \quad i = 1, 2, \ldots, j \tag{3}$$

$$d_n^{(i)} = \sum_{k=0}^{N-1} h_k a_{2n-k}^{(i-1)} \quad a_n^{(0)} = x_n \tag{4}$$

When $a_n^{(i)}$ is approximation coefficients in component i of low pass filters and $d_n^{(i)}$ is detail coefficients in component i of high pass filters. For input signal N and the coefficient of the low-pass filter (g_k) and high pass filter (h_k) defined by the mother wave function [34]. The Daubechies 6 function (db06), which has a signal structure resembling the ECG signal, was used for this study [35].

3. ECG SIGNAL PROCESSING ALGORITHM ON NODE MCU

An algorithm for ECG signal analysis using wavelet transform techniques on a node MCU microcontroller consists of five blocks: ECG signal acquisition, moving average, wavelet transform, peak detection, and heart rate calculation, as shown in Figure 1. The signal acquisition function stores the ECG signal (block 1), which has a frequency of 125 Hz, in a data array. The data array requires two R-peaks for heart rate calculations. To accurately capture both peaks of the heart rate data, a minimum of 200 data points need to be collected in the array. Nonetheless, if the number of arrays is fewer than 200, it is possible that two R-peaks may not be present in the louder array, potentially leading to erroneous heart rate calculations by the algorithm. The captured ECG signal is affected by two types of noise: baseline noise, caused by breathing or body movements, which has a low frequency, and wideband noise, caused by muscle artifacts and instrumentation noise. Baseline noise and wideband noise are two types of noise that can affect the quality of an electrocardiogram (ECG) signal. ECG is a vital medical test used to record the electrical activity of the heart over time. Noise in the ECG signal can obscure important information and make it difficult to interpret the results accurately. Therefore, both signals are incorporated into the original data for processing, allowing us to assess the effectiveness of our proposed algorithm. Hence, within the program designed for embedded into the microcontroller, it utilizes a total of 54,886 bytes of global memory (equivalent to 67% of the total memory). In our simulation, all 10-second ECG signals are stored on an external memory card. The Node MCU reads the data from the memory card and stores it in a data buffer as if it were reading from an ECG sensor. When executing a single cycle of the program to process ECG signals, the average total execution time is 249 milliseconds. This duration is deemed suitable for real-time display should the algorithm be employed in real-life scenarios in the future.

The moving average function (block 2) is an alternative form of averaging that differs from the conventional averaging method in which all data are averaged. Moving averages employ a fixed number of windows to average and shift the windows according to the position of the data. In signal processing, moving averages are utilized to smooth signals from short-term overshoots or fluctuations caused by noise, serving as a high-pass filter. However, there exist filters that are more effective than moving average filters but are also more complex and unwieldy. Thus, to reduce complexity and processing time to suit the capabilities of the node MCU, this article utilizes a moving average for baseline noise elimination. Figure 2 illustrates the working process of the moving average function. The process begins by initializing the window size to 49 and calculating the mean of the data in the window range. By adjusting the size of the moving window, you can control the degree of noise reduction versus the level of detail preservation. Larger window sizes result in greater noise reduction but can also smooth out genuine signal variations. Window scaling experiments show that a window size of 49 is suitable for eliminating low-frequency noise generated in ECG signals. A window size of 49 was chosen for the implementation of the moving average filter to effectively mitigate low-frequency noise, such as baseline noise, in our simulations. The mean is computed using the position of the data as the middle position of that window, and the position of the data is shifted until it reaches the data in the last position. As a result of the moving average, we obtain a signal that resembles baseline noise. Consequently, when we subtract this signal from the noisy ECG signal, we eliminate the baseline noise. However, it is important to note that while moving average filters are effective for reducing low-frequency noise, they may not be as effective at removing high-frequency noise or preserving sharp transitions in the signal. The choice of filter type and parameters should be based on the specific characteristics of the noise and the desired signal fidelity. Hence, an additional step is necessary to eliminate noise by employing wavelet transform.

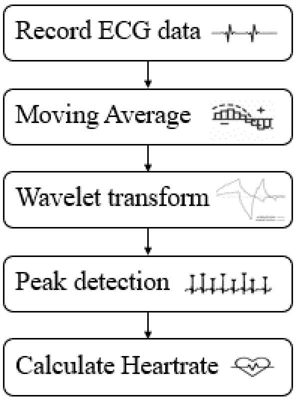

Figure 1. Flow diagram of algorithm ECG signal processing on Node MCU

```
Initialization: window=49, sum=0, k=0
   for i=0 until i<length of ECG_noise
            for j= -(window-1)/2 until j=(window-1)/2
                   if (i-j) not in range of ECG_noise
                          do nothing;
                   else
                          sum=sum+ECG_noise(i-j);
                          k=k+1;
                   end if
            end for
            base_line(i)=sum/k;
            ECG_remove_baseline(i)=ECG_noise(i)-base_line(i);
            k=0;
   end for
```

Figure 2. Pseudo code of moving average part

In wavelet transform function (block 3), a wideband noise elimination technique using wavelet transform is employed. The wavelet transform is utilized to decompose a signal into its frequency components, similar to the Fourier transform. However, the Fourier transform only provides the frequencies contained in the signal and may not be applicable to all signals, such as ECG signals with sudden changes of short duration. In contrast, wavelet transformation separates time-domain signal components by utilizing two fundamental properties: scale and location. While the Fourier transform primarily provides frequency information, the wavelet transform exhibits a distinct advantage when applied to signals characterized by abrupt, short-duration changes, as is often the case with ECG signals. It is worth emphasizing that the wavelet transform provides a dual perspective, offering insights into both frequency and time-domain characteristics, rendering it particularly well-suited for the comprehensive analysis of ECG signals. Moreover, wavelet transformations reduce the size of the data to half of the original size while preserving all important characteristics. Therefore, wavelet transform was chosen to eliminate wideband confounding. Figure 3 illustrates the discrete wavelet transform utilizing the convolution principle. The input signal (*x*) that has been processed with baseline noise is convolved with the signal *h*, which is the filter coefficient of the mother wavelet. The convolution process results in a signal with a length of (*x*) + *length* (*mother wave*) – 1. Only the odd-numbered indices, which are the sum of the low-frequency component signals, are selected from this result, known as the approximation coefficients. The approximation coefficients eliminate wideband noise and reduce the size of the ECG signal by half, while preserving its essential characteristics. This process also reduces the time required to calculate the maximum peak in the next step.

```
Initialization: Size of variable x, y, z =length of (x+h)-1
        for i=0 until i<length of x
                for j=0 until j≤i
                        y(i)=y(i)+x(j)*h(i-j);
                end for
        end for
                ECG_decomposition=odd index of y
```

Figure 3. Pseudo code of wavelet transform part

The function 4,5 in ECG signal processing is peak detection (block 4) and the calculation of the heart rate (block 5) value of the data set. As the ECG signal data stored in the array (ECG_decomposition array) only has two peaks, we can split the data into two parts and determine the maximum value in each segment. The highest value in the first part corresponds to the highest peak R_1, and the highest value in the second part corresponds to the highest peak R_2. The program will then store the position of each peak value. The position values of the two R peaks are subsequently subtracted to determine the time difference, which is then multiplied by 0.016 ($\Delta T=1/62.5$) to find the heart rate frequency, expressed as the number of beats per minute by multiplying by 60 seconds. This process is show in Figure 4.

```
Initialization: peak_1=0; peak_2=0;
                Pos_peak1=0; Pos_peak2=0;
     for i=0 until length(ECG_decomposition)/2
        if ECG_decomposition(i)>peak_1
             Pos_peak1=i;
        end if
     end for
     for i=length(ECG_decomposition)/2 until length(ECG_decomposition)
        if ECG_decomposition(i)>peak_2
             Pos_peak2=i;
        end if
     end for
     HR=(1/(Pos_peak2-Pos_peak2)*0.016)*60;
```

Figure 4. Pseudo code of peak detection part and heartrate calculation

4. RESULTS AND DISCUSSION

As part of the experimental and performance analysis, as well as validation of the algorithm for analyzing ECG signals using the wavelet transform technique developed for use on the node MCU board presented in this article. We have divided the experiment into two parts to study the efficiency of using the wavelet transform principle for noise elimination in ECG signals. Part one validates the noise elimination algorithm for node MCU compared to reliable wavelet transform programs. The second part examines the algorithm's performance against the normal human heart rate range (65-85 bpm), and analyzes and tests the performance of the selected mother wavelet for synthetic ECG signal analysis.

To validate the ECG signal analysis algorithm employing the wavelet transform method implemented on the node MCU board, we performed a comparative analysis of the results with a widely recognized function in the reliable computer programs, known for its established credibility in ECG signal analysis. Figure 5 illustrates an example of the comparative results, showing that the ECG signal analysis algorithm utilizing the wavelet transform technique, executed on the node MCU board, exhibits similarities to the use of pre-existing functions in reliable computer programs, with a correlation coefficient of 0.99. The correlation coefficient indicates that the ECG signals processed by the algorithm running on the node MCU exhibit similarity to those processed using the function within the robust program. This observation serves as empirical evidence supporting the correctness and suitability of the wavelet transform algorithm implemented on the node MCU for ECG signal analysis.

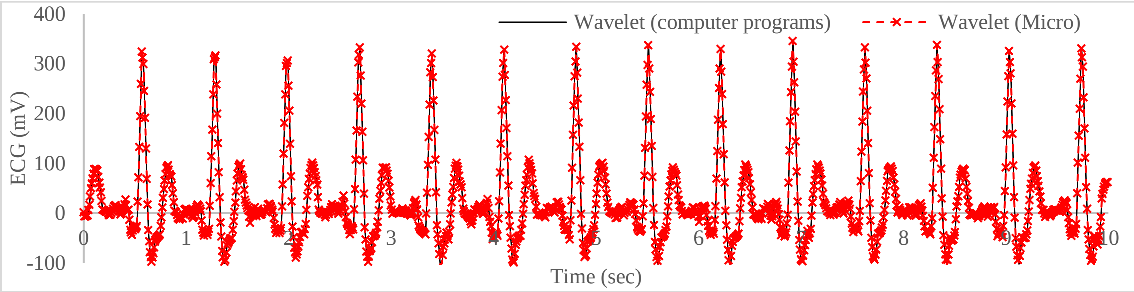

Figure 5. Comparison of the results of wavelet (Micro) with the function of computer programs

The second part of our study aims to analyze the selection of an appropriate mother wavelet for processing ECG signals without interference to validate the true capabilities of the ECG signal processing algorithms. To simulate pure ECG signals without any interference, we generated a simulated ECG signal with varying heart rates of 65, 70, 75, 80, and 85 beats per minute at a sampling frequency of 125 Hz. Investigating algorithm efficiency often involves introducing noise to the original signal. In a previous study [36], noise was incorporated within a range of -12 to 12 dB to assess the performance of beat detection algorithms. In our current research, we have introduced two specific types of noise: baseline noise with an amplitude of 50 mV and wideband noise with a power level of 15 dB. Figure 6 provides an example of a simulated ECG signal with a heart rate of 85 beats per minute. Figure 5 has been to visually represent the ECG signal illustrating the efficacy of a window size of 49 in effectively eliminating the baseline noise in Figure 6.

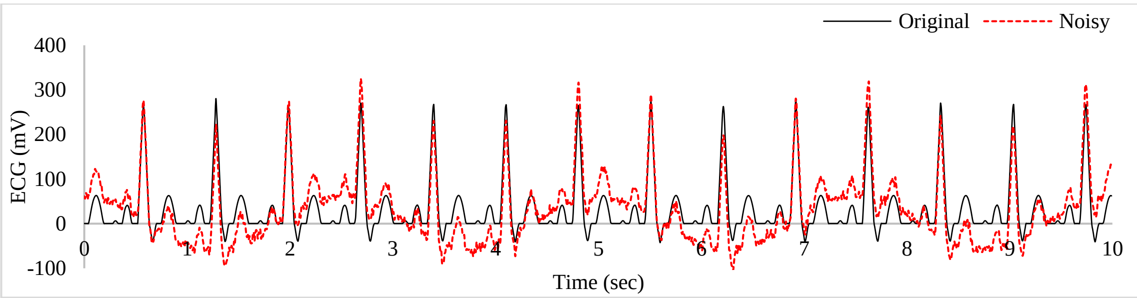

Figure 6. Synthetic ECG and Noisy synthetic ECG with heart rate 85 bmp

As mentioned earlier, the wavelet transform method relies on wavelet coefficients that function as weights for each frequency component level. Therefore, it is essential to select a coefficient function for the mother wavelet that is suitable for the signal being processed. However, previous studies have shown that the use of different mother wavelets for ECG signal analysis yields varying performance results. Since ECG signal analysis and noise elimination are typically performed on computers with ample computational resources, wavelet transform method can be applied at multiple levels to obtain the best possible signal. However, due to resource constraints on microcontroller boards, the ECG signal analysis algorithm presented here only performs a one-level wavelet transform. Therefore, to determine the most efficient and suitable mother wavelet for the ECG signal analysis algorithm, we apply the wavelet transform method on a microcontroller board. We evaluate the performance of several commonly used mother wavelets, including db4, db5, db9, coif5, bior3.3, and Sym4, which have demonstrated high efficiency in past research. Additionally, we test the basic mother wavelet Haar, which has the fewest coefficients among the mother wavelets and requires less memory, to assess its performance and compare it with the other mother wavelets commonly used for analyzing ECG signals. The choice of mother wavelets, including Harr, db4, db5, db9, coif5, bior3.3, and Sym4, for evaluating their performance in ECG noise elimination is based on several factors relevant to wavelet analysis and signal processing. These wavelets are part of a broader family of wavelets with distinct properties, and their selection is motivated by various considerations. Firstly, the selected wavelets belong to different wavelet families (e.g., Daubechies, Coifman, Biorthogonal, Symlet), each characterized by unique properties and filtering capabilities. This diversity enables us to investigate the influence of various wavelet families on the efficacy of ECG noise elimination. Figures 7 to 13 depicts a comparison between the original ECG signal and the ECG signal processed to eliminate noise by the wavelet transform method using different mother wavelets, namely Harr, db4, db5, db9, coif5, bior3.3, and Sym4. As observed from the figure, the signal processing technique successfully eliminates the baseline noise with an amplitude of 50 mV. However, for the wideband noise, the power of 15 dB can be eliminated but still leaving a little amount. Moreover, the wavelet transform method resulted in higher amplitude peaks of ECG signals Q, R, S, and T. However, the lowest amplitude P peak, which is close to the amplitude of the wideband noise, is almost absent.

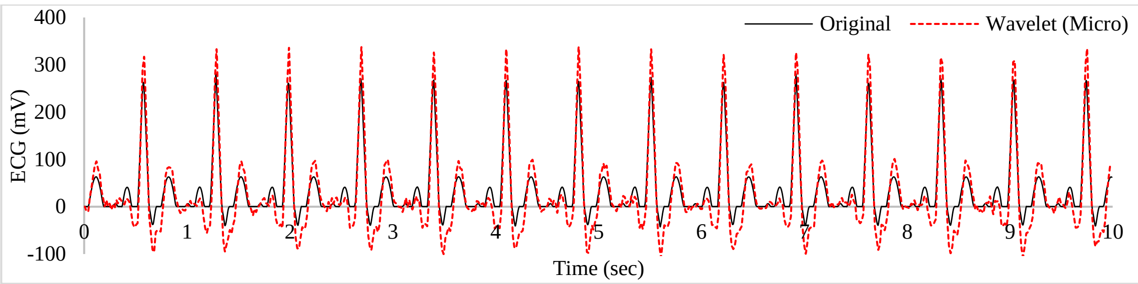

Figure 7. Result of ECG data processing algorithm using Harr wavelet with heart rate 85 bmp

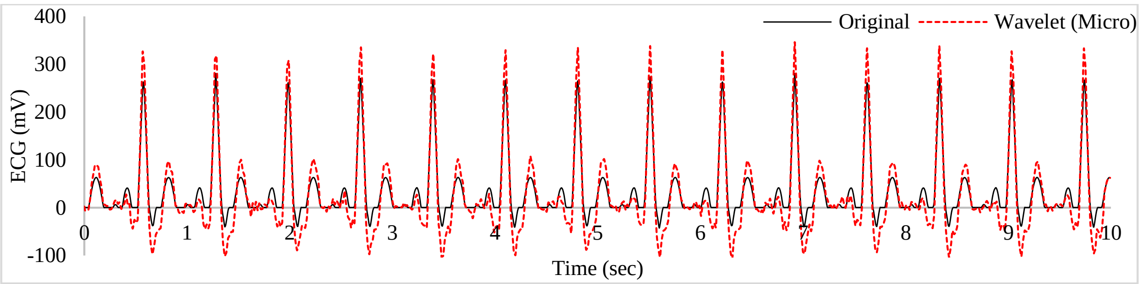

Figure 8. Result of ECG data processing algorithm using db4 wavelet with heart rate 85 bmp

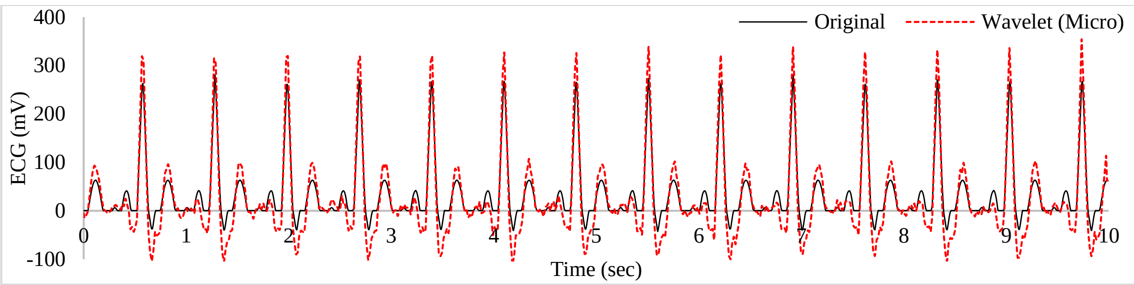

Figure 9. Result of ECG data processing algorithm using db5 wavelet with heart rate 85 bmp

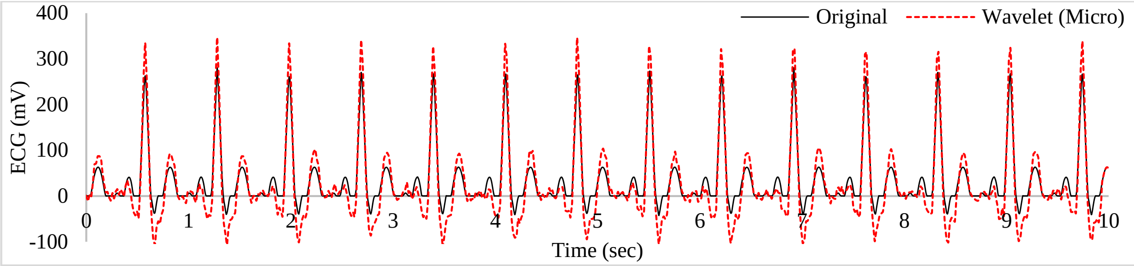

Figure 10. Result of ECG data processing algorithm using db9 wavelet with heart rate 85 bmp

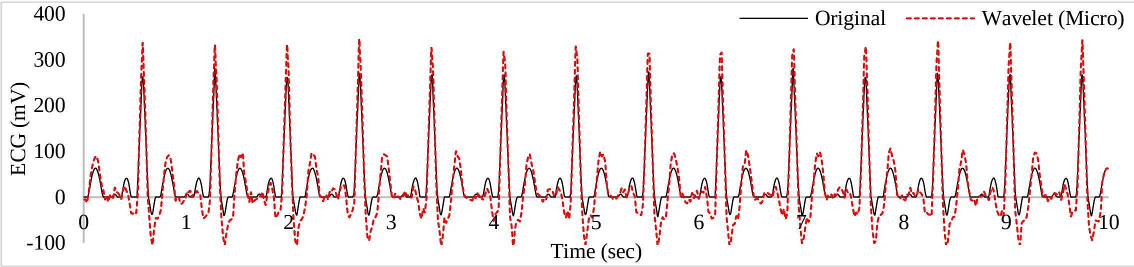

Figure 11. Result of ECG data processing algorithm using coif5 wavelet with heart rate 85 bmp

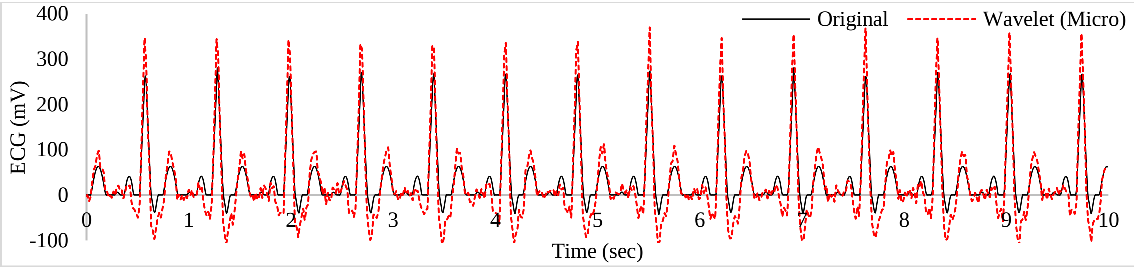

Figure 12. Result of ECG data processing algorithm using bior3.3 wavelet with heart rate 85 bmp

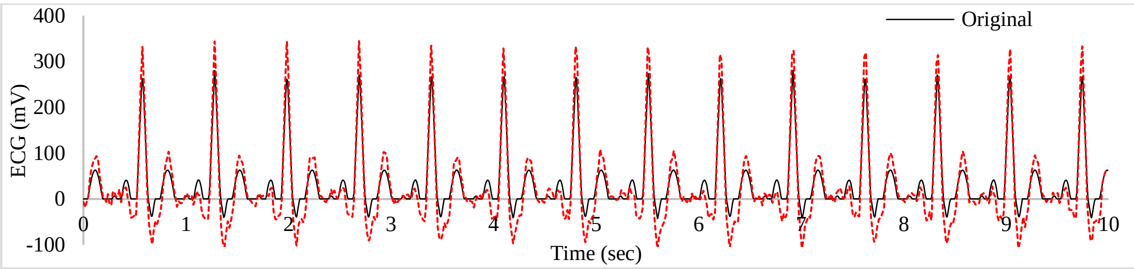

Figure 13. Result of ECG data processing algorithm using Sym4 wavelet with heart rate 85 bmp

We consider the simulated ECG signal as a pristine reference signal, characterized by its cleanliness and clarity. This reference signal is subsequently subjected to the addition of both baseline and wideband noise, thereby serving as a benchmark for evaluating the efficacy of the noise removal algorithm based on the wavelet transform principle. To substantiate the effectiveness of ECG signal processing employing the wavelet transform principle and to select the appropriate mother wavelet, we rely on quantitative measures frequently employed in prior research. These measures encompass signal-to-noise ratio (SNR), correlation coefficients between the original ECG signals and the processed signal (r), as well as the root mean square error (RMSE), as defined by (5) to (7):

$$SNR(db) = 10log_{10}\left(\frac{\sum_{n=0}^{N-1}[s_o(n)]^2}{\sum_{n=0}^{N-1}[s_{re}(n)-s_o(n)]^2}\right) \tag{5}$$

$$r = \frac{\sum_{n=0}^{N-1}(s_o-\overline{s_o})\cdot(s_{re}-\overline{s_{re}})}{\sqrt{\sum_{n=0}^{N-1}(s_o-\overline{s_o})^2\sum_{n=0}^{N-1}(s_{re}-\overline{s_{re}})^2}} \tag{6}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1}(s_{re}(n)-s_o(n))^2} \tag{7}$$

when s_o is the original ECG signal and s_{re} is the processed ECG signal.

The SNR is a measure of the quality of a signal, indicating how much the signal power in a given signal compares to the noise power. Figure 14 show the SNR of each mother wavelet used with different heart rates, ranging from 65 to 85 bpm in increments of 5 bpm. The results indicate that the SNR of every mother wavelet increases with increasing heart rate. Among the mother wavelets, the db4 wavelet exhibited the highest SNR values for heart rates of 65, 70, 80, and 85 bpm, with values of 6.44, 6.67, 6.93, and 7.06, respectively. In contrast, the db9 wavelet yielded the highest SNR at 75 bpm with a value of 6.90, while the bior3.3 wavelet had the lowest SNR values overall. Figure 15 presents the average SNR values of all heart rates to determine the mother wavelet that yielded the highest SNR. The db4 wavelet yielded the highest mean SNR of 6.77, while the bior3.3 wavelet had the lowest mean SNR of 5.83. Heart rate, denoting the frequency of heart beats per minute, serves as a fundamental physiological parameter. A higher heart rate signifies an increased rate of cardiac contractions, resulting in a greater number of cardiac cycles occurring within a specified temporal interval. In the context of ECG data, each cardiac cycle manifests as a distinctive pattern characterized by key waveforms, including the P-wave, QRS complex, and T-wave. These waveforms, collectively termed fiducial points, hold invaluable diagnostic information. Elevations in heart rate correspond to a heightened occurrence of cardiac cycles per unit of time. Consequently, the fiducial points (P, QRS, T) materialize more frequently within the ECG signal. This heightened frequency enhances their distinctiveness amidst the backdrop of potential noise, thereby augmenting the SNR within the ECG signal.

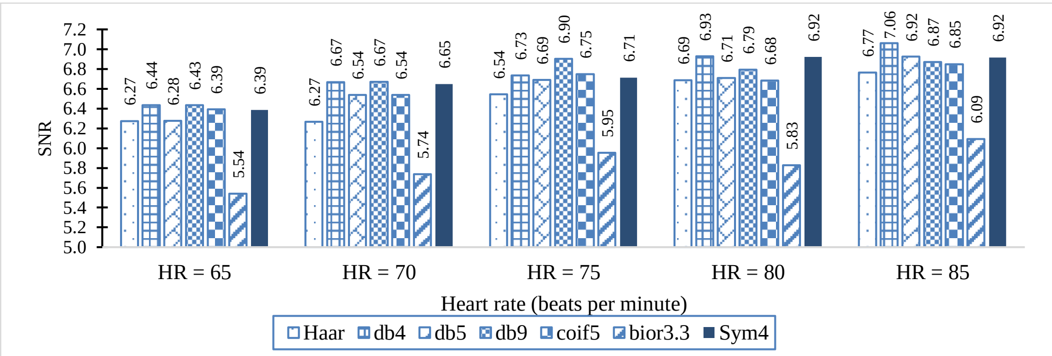

Figure 14. SNR of mother wavelets with different heart rates

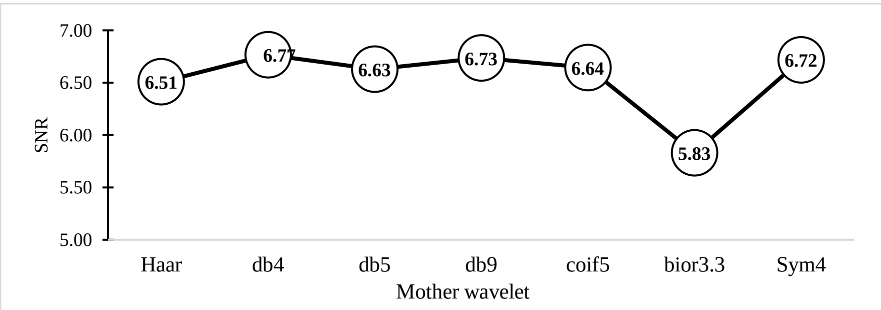

Figure 15. Comparison between the mother wavelet in terms of the mean SNR

Figure 16 show the correlation coefficient between the original ECG signal and the processed ECG signal, wherein a value close to 1 indicates that the signal processing algorithm can eliminate a significant amount of noise and that the processed ECG signal is similar to the original signal. From Figure 16, it was observed that as the heart rate increased, the correlation coefficient also increased. This observation corresponds to the SNR illustrated in Figure 14 because a high SNR indicates that the algorithm can eliminate noise and leave only the original ECG signal, resulting in a high correlation coefficient. Upon considering each mother wavelet, it was found that all mother wavelets yielded similar correlation coefficients. However, db4, db9, coif5, and sym4 produced the highest correlation coefficients. Figure 17 shows the average correlation coefficients of all heart rates, which demonstrated that the mother wavelet with the highest correlation coefficient, db4 was 0.955. Figure 18. illustrates the RMSE for each heart rate. It was discovered that when heart rates were at 65, 80, and 85, the utilization of the mother wavelet db4 resulted in the lowest RMSE values of 28.95, 30.23, and 30.69, respectively. Meanwhile, the mother wavelet db9 resulted in the lowest RMSE values at heart rates of 70 and 75, with values of 28.71 and 29.24, respectively. On the other hand, the mother wavelet bior3.3 produced the highest error, which is consistent with the SNR and the lowest correlation coefficient. Figure 19. illustrates the average RMSE across all heart rates, which was found to be the lowest for db4 at 29.74. A suitable mother wavelet for ECG signals depends on several factors, including the characteristics of the ECG signal, the required resolution in time and frequency domains, and the specific application of interest. One commonly used mother wavelet for ECG signals is the Daubechies wavelet. It has a compact support, which means that it is localized in time and frequency domains. This property makes it well-suited for analyzing signals with abrupt changes, such as ECG signals that contain QRS complexes. Another commonly used mother wavelet for ECG signals is the Symlet wavelet. It has similar properties to the Daubechies wavelet but with slightly better time-frequency localization. Other wavelets that can be used for ECG signal analysis include the Coiflet wavelet, the Biorthogonal wavelet, and the Harr wavelet. The choice of the mother wavelet can also depend on the specific application of interest. It is important to note that the choice of the mother wavelet is not the only factor that determines the performance of wavelet-based ECG signal analysis methods. Other factors such as the decomposition level, thresholding method, and feature extraction techniques should also be considered.

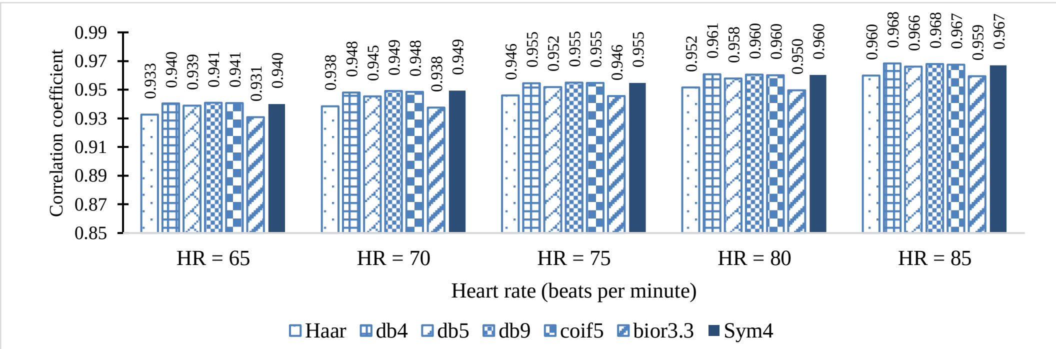

Figure 16. Correlation coefficient of mother wavelets with different heart rates

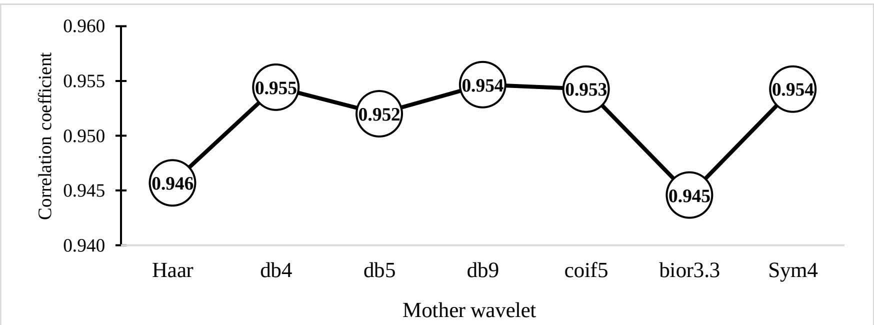

Figure 17. Comparison between the mother wavelet in terms of the mean correlation coefficient

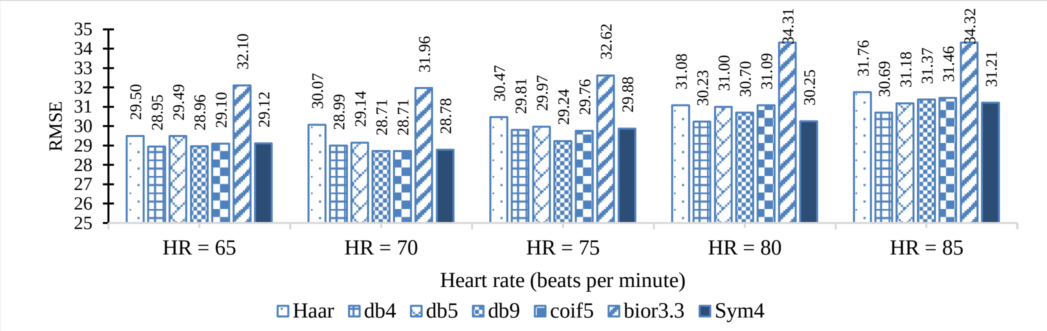

Figure 18. RMSE of mother wavelets with different heart rates

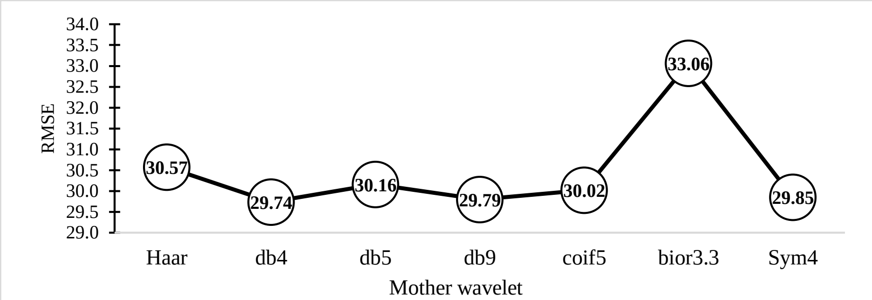

Figure 19. Comparison between the mother wavelet in terms of the mean RMSE

In the context of R-wave identification, our algorithm stands out as a straightforward and efficient solution suitable for implementation in microcontrollers. It exhibits a commendable ability to precisely pinpoint the R-peaks within the array data, enabling us to subsequently compute the temporal separation between these R-peaks in alignment with the data sampling frequency. However, it is worth noting that more sophisticated algorithms, as referenced in [22], [23] are available for the accurate localization of QRS peaks. When such algorithms are applied to determine the positions of these peaks with precision, the timing of these peak occurrences can prove valuable in the diagnosis of heart diseases.

5. CONCLUSION

The article describes a study on the use of wavelet transform principles for analyzing ECG signals to eliminate interference that may occur during measurement. The article presents an algorithm that can eliminate interference using wavelet transform principles processed in a node MCU and a peak detection algorithm for calculating heart rate. The algorithm was tested on both simulated and real ECG signals using parameters such as SNR, correlation coefficient, and RMSE to evaluate performance. In the study of the performance of the ECG signal processing algorithm, we conducted two tests. The first test aimed to validate the accuracy of the wavelet transform algorithm used in the node MCU by comparing it with the computer program’s built-in function. The results showed that the algorithm was accurate with a correlation coefficient of 0.99. The second test aimed to determine the most suitable mother wavelet for selecting heart rate in the range of 65-85 beats per minute, which is the normal human heart rate. The db4 mother wavelet was found to be the most suitable, based on the best values of average SNR, correlation coefficient, and RMSE, which were 6.77, 0.954, and 29.74, respectively. The results showed that the most appropriate mother wavelet for signal processing in the simulation model was the db4 wavelet, which provided the highest average SNR and correlation coefficient values. The db9 wavelet also provided a low average RMSE value and SNR and correlation coefficient values that were similar to those of the db4 wavelet. In this paper, we demonstrate the feasibility of implementing complex algorithms, such as the wavelet transform, for ECG noise elimination on a small microcontroller. Furthermore, the test results demonstrate the accurate performance of the algorithm for detecting the two R-peaks within the ECG array data, facilitating precise heart rate calculations. Furthermore, we present the results obtained from employing various mother waveforms to analyze and assess their efficiency. However, due to memory constraints, the frequency sampling rate was limited to 125 Hz, and the filter bank output frequency was reduced by half. This resulted in the wavelet transform being performed on only one level, which allowed some noise to remain in the signal. Increasing the sampling rate or using more complex multiresolution algorithms to process the signals would be a challenge in future research. Finally, the proposed algorithm prototype exhibits significant potential for a diverse range of applications that extend beyond the realm of remote medicine. Notable among these applications are the utilization in wearable health devices, remote monitoring, health and wellness Apps, healthcare facilities in resource-limited areas, education and training, as well as home monitoring for chronic patients. These identified applications underscore the algorithm's adaptability and its capacity to thrive within a spectrum of healthcare and medical technology contexts, rendering it an asset for advancing cardiac care and diagnosis. Within the constraints of price accessibility to the general public and the requisite quality standards.

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