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Performance Evaluation of Hybrid VS/WF Techniques for Precise Analysis of Cardiac Arrhythmias

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Abstract: One of the most vital portions of the humanoid body is the heart, which circulates blood throughout the body and transports oxygen, nutrition, and waste products. Yet, the shift in lifestyle and environmental aspects results in an aberrant heart's ability to beat. Cardiovascular diseases (CVDs) are the leading reason of demise worldwide and the biggest health concern in the modern world, impacting people of all ages. Heart and blood vascular illnesses are grouped together as CVDs. Cardiovascular diseases include cardiac arrhythmias (CAs), which are primarily categorized as atrial and ventricular arrhythmias. Around 61% of the world's population has a CVD, according to WHO estimates. ECG is primarily utilized to diagnose CAs, despite the fact that a variety of medical tools including phono cardiography, ECG (electrocardiography), etc. are obtainable to analyze cardiac problems. This is a low-cost, non-invasive instrument that is accessible in both rural and urban primary health centers. Power-line noise, baseline wander noise, and other environmental contaminants frequently corrupt the ECG signals. In all medical methods, signal degradation brought on by artifacts is quite common and tends to change the signal pattern. As a result, there has been a rise in the need for cutting-edge equipment to perform precise ECG analysis and parameter evaluation. Thus, it is essential to create a model for accurate ECG analysis.

Keywords: *CVD, CA, PCG, ECG.*

1. Introduction

It takes a lot of determination and time to physically assess cardiac arrhythmias through an ECG signal because there are so many cardiac patients. Also, it becomes difficult for doctors to identify the initial arrhythmia episodes and administer prompt treatment at an early stage in cases with significantly high-risk arrhythmias. The difficulties that doctors encounter inspire the development of bio-medical digital signal processing [1]. As a result, it is clear that the analysis of bio-medical digital data presents a difficult problem for academics. The accuracy, speed, and non-invasive clinical procedures have all significantly increased. These modifications aid and facilitate the doctor's duty of identifying the issues [2].

HVS (Hybrid Visu Shrink)/WF (Weiner Filter) and TNN (Thresholding Neural Network) are two de-noising algorithms that are suggested. The benefit of a wavelet-founded VS technique is paired with WF in the fusion VS/WF method. A variety of noise sources, including Electromyogram (EMG), and several quality measures are used to assess how well the Hybrid VS/WF approach performs. As compared to more traditional thresholding techniques like different methodology performs better [3].

The sole tool that can analyze and identify heart rhythms is the inexpensive, non-invasive ECG as shown in Figure I. The study of the ECG signal effectively conveys important clinical data about the heart's rhythm, shape, and regularity. The ECG measures the P, QRS, and T waves as electrical signals travel through the various heart chambers [4]. Any variation in the beginning of the atrium and ventricles reflects the typical sinus rhythm. The electrocardiogram (ECG) is used to identify cardiac arrhythmias, which are irregularities, disruptions, or anomalies in the heart's rhythm. It is used to identify cardiac conditions with a very high risk of occurring, such as myocardial infarction, heart attacks, and congestive heart failure [5]. Dysrhythmia refers to any irregularity in rhythm or interference with the heart's regular rhythmic contraction. Nonetheless, dysrhythmia and arrhythmia are frequently used in the same sentence [6].

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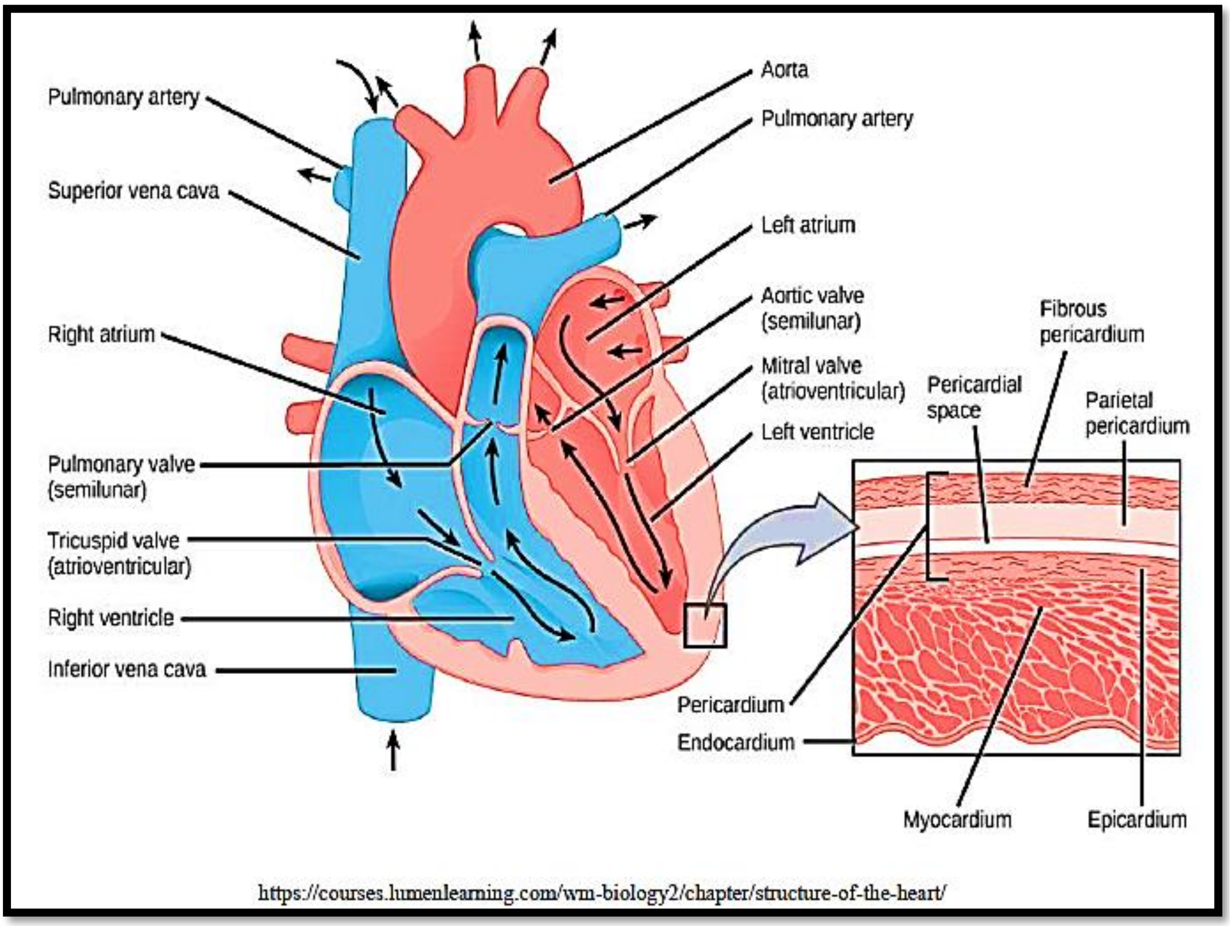

Fig I: Heart structure Diagram.

Typically, several disturbances and artifacts that are present in the ECG signal's frequency band interfere with the recorded ECG signal [7]. The following significant noises cause the ECG signal to be distorted: Power line interference is a result of the experiment's electromagnetic (EM) wave-filled environment. Due to incorrect grounding, the 50Hz (India) power line interference corrupts the ECG signal. The power supply's alternating current (AC) is what creates the fundamental frequency [8].

The term "baseline wander" (BLW) refers to a common type of noise that can be found in biological signals in general. A shift in the chest that is caused by coughing or just breathing leads to ECG signals, which is what produces this. When there is a considerable movement of the chest, or when an arm or leg is moved during the collection of an ECG using limb leads [9]. Alterations in temperature and bias within the amplifiers and instruments have the ability to bring up this type of noise. In the majority of instances, the contraction of a muscle is brought on by zero-mean band-limited transitory bursts. Rapid volatility is caused by interference in electromyograms (EMG), which outpaces the ECG wave in terms of speed. When an electrode is moved, it can generate transient fluctuations in the skin impedance of the electrode [10], which are known as motion artefacts. The peak amplitude of the motion artefact is 500 percent higher than the peak-to-peak amplitude of the ECG, and its duration ranges from 100 milliseconds to 500 milliseconds. Moreover, the motion artefact has a peak amplitude. An adaptive filter can be used to cut down on the interference caused by motion artefacts. Electrode contact noise is caused when the skin electrode and the ECG leads do not make a tight enough contact with one another. Recordings of an electrocardiogram (ECG) may contain a large amount of noise because of the subject's movements and a loose electrode that is brought back into and out of contact with the skin. Power line interference could be observable in the electrocardiogram recording even though there will be no current flowing through the skin when the connection is broken [11].

2. Related Work Done:

It is absolutely necessary to have a complete comprehension of the operations of the human heart, as well as the arrhythmias of the electrocardiogram and the processing of medical signals. One of the primary contributors to the increase in the number of deaths across all age groups is the incidence of cardiac arrhythmias

(CAs). Atrial and ventricular arrhythmias are caused by a malfunction in the firing mechanism of the atrial and ventricular cells [12]. These arrhythmias can lead to excessive blood pressure, heart attacks, and other health complications. An electrocardiogram provides a very detailed picture of any abnormal heart activity occurring in the atrial and ventricular chambers. Atrial arrhythmia is the medical term for an irregular heartbeat that originates in either of the two upper chambers of the heart, also known as the left and right arteries of the atrial conduction pathways. Atrial arrhythmias can cause a variety of symptoms, including shortness of breath, palpitations, a feeling of pressure in the chest, and an excessively rapid pulse [13]. The method of de-noising known as the Hybrid Visu Shrink (VS)/Weiner Filter (WF) is one that is suggested in this paper. In the fusion VS/WF method, the advantage of a wavelet-founded VS technique is linked with the benefit of using WF. The effectiveness of the Hybrid VS/WF technique is evaluated using a number of different noise sources and a few different excellence events. One of these noise sources is the electromyogram (EMG). As compared to thresholding methods that are considered to be more traditional, the Hybrid VS/WF methodology performs significantly better [14].

A select group of researchers applied an IIR filter to the electrocardiogram in order to get rid of a sizeable portion of the baseline wander noise. According to what they said, the FIR filter requires a higher level of processing sophistication, as well as higher memory and power requirements. They arrived at the conclusion that IIR filters are less complicated to put into action and require fewer computational resources than FIR filters [15-16]. Another group of employees indicated that FIR and IIR filters were developed in order to reduce noise from a number of sources, such as electromagnetic field noise (EMG noise), interference from power lines, and baseline drift. They have discovered that the linear phase property of FIR filters makes them the optimum choice for processing ECG signals [17]. This was discovered through their research. However, there must be a greater number of filter layers than before, and this results in a proportional increase in the signal's delay. The use of IIR filters is acceptable because they require just a limited number of filter orders, which results in a reduction in both the complexity of the hardware and the cost of the calculation [18-20].

A novel electrocardiogram (ECG) enhancement strategy based on empirical mode decomposition was proposed by a number of researchers (EMD). It has been noted that their method removed baseline wander in addition to high-frequency noise while creating the least amount of signal distortion [21]. This was achieved despite the fact that it did cause some signal distortion. Experiments conducted using the MIT-BIH database are used in order to verify the methodology. The findings are given to the reader in a format that is both quantitative and qualitative. [Citation needed] The simulations demonstrate that the EMD-based technique that was provided yields extremely satisfying outcomes when it is applied to the task of noise reduction. According to the findings of their research [22], EMD is a superior technique for denoising electrocardiograms when compared to other, more standard filter methods.

The findings are examined via the prism of the noise-free reconstruction quality possessed by the universal threshold [23]. It is strongly suggested that sub-band adaptive thresholding be used whenever it is at all possible. A technique known as the difference in the mean is utilized in the process of determining which values should be utilized for the operation's parameters. A wide array of electrocardiogram (ECG) signals are incorporated into MATLAB models. The findings demonstrate that the thresholding strategy that was proposed works more effectively than the solutions that are being utilized at the moment [24].

Analysis of non-stationary signals can benefit greatly from time-frequency analysis, which involves separating the signal into its time and frequency components. The time domain has high time resolution but no frequency resolution, therefore it only tells you about the signal's amplitude and duration. Hence, the frequency domain provides a wealth of detail about the signal's spectral composition but little insight into the signal's temporal evolution (owing to its lack of time resolution and high frequency resolution).

The Time-Frequency domain is a transition zone between the two, delivering both temporal and spectral details concurrently. Because of this characteristic, ECG signals may be represented and analyzed effectively in the Time-Frequency domain. These days, the Wavelet transform is frequently employed in signal processing for Time-Frequency domain analysis [25]. With a single transformation, wavelet-based signal processing is able to single out specific time and frequency components of a signal. It can be put to use in a wide variety of contexts, including signal coding, signal de-noising, wave detection, feature extraction, etc.

The objective of the proposed work

The main objective of this work is to investigate Hybrid VS/WF, for accurately analyzing cardiac Arrhythmias.

The following goals are attained in order to reach this goal.

1) Enactment assessment of a Fusion VS/WF method for operative ECG signal noise lessening.

2) To study the effects of noises on ECG patterns.
3) To study the noises in the ECG signal and techniques to remove them.

3. The Proposed Work:

To combine the best of the Weiner filter and the Wavelet transform-based Visu Shrink method, a novel approach is offered. The Weiner filter is created with the use of a wavelet shrinkage estimate. Significant QRS complex extremes are preserved, and the signal is realized without artefacts using this method as presented in Figure II. Minimizing the mean squared error (MSE) is easiest to achieve with the Wiener filter. An inverse transform is performed on the filter's output after applying the wavelet coefficients from the noisy signal to the coefficients of the Wiener filter in order to reconstruct the estimate signal. First, the theta and variance must be estimated in order to create the Wiener filter.

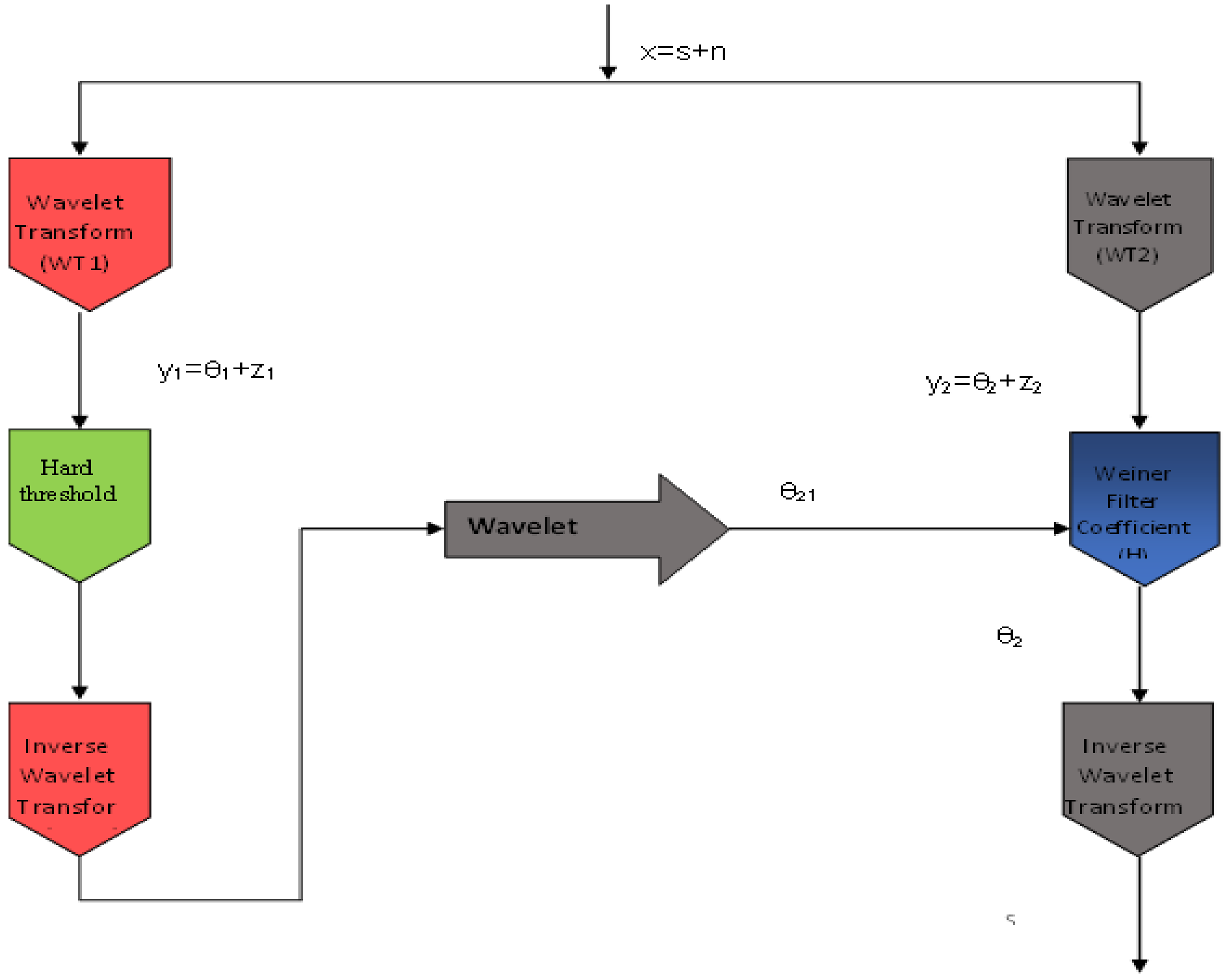

Fig II: Block diagram of the projected Fusion VS/WF pre-processing method.

Coefficients of the wavelet transform are used to create an estimate of the variance. Wavelet Transform is first used to deconstruct the noisy ECG signal x(i) into more manageable levels. After that, the produced hard threshold coefficients only keep the trustworthy (N) t coefficients with a high SNR and throw away the rest.

4. Result and Discussion:

The algorithms' efficacy is evaluated with respect to the following criteria. It is possible to foretell the predicted signal quality using these factors. How much noise is eliminated and how well the predicted signal matches the actual signal is determined by these metrics.

1.1. Mean Square Error: A popular unit of measurement. It is the sum of the squares of the differences between the estimated ECG signal and the original, noise-free ECG signal. The signal quality evaluation method is straightforward and frequently employed. The MSE of a filter is considered to be optimal if it has the lowest possible value.

$$MSE = \frac{1}{XY}\sum_{i=0}^{X-1}\sum_{j=0}^{Y-1}[B(i,j) - b(i,j)]^2 \quad (1)$$

1.2. Peak Signal to Noise Ratio: PSNR is the gold standard. The ratio between the squares of the original and estimated ECG signals is provided by

$$PSNR = 10.log_{10}\frac{Max_i}{\sqrt{MSE}} \quad (2)$$

1.3. The Artifact to Signal Ratio (ASR) is a statistic that compares the estimated strength of the ECG signal to the power of any artefacts present in the data. If the ASR is high, then the artefact removal technique works well.

$$ASR = \frac{\sum_{i=1}^{N}(x_i - s_i)^2}{\sum_{i=1}^{N} s_i^2} \quad (3)$$

Only data with a high artefact contamination rate can benefit from the ASR criterion. A greater ratio does not necessarily indicate better artefact removal for data that does not contain artefacts.

1.4. The smoothness of the estimated ECG signal is quantified with a Smoothing Index (SI). Specifically, it is the ratio of the estimated ECG signal to the actual ECG signal.

The ECG signals used in the implementation of these methods come from the MIT-BIH database. After subtracting the value with base and dividing by gain, the raw units are transformed into physical units. As a means of standardizing on a single sampling rate, we resample all signals under consideration to 360Hz. We use the data from ECG patient 103's chart, with the signal length set to 500 samples. It is seen in Figure III below that 20% AWGN is added to the signal to approximate EMG noise.

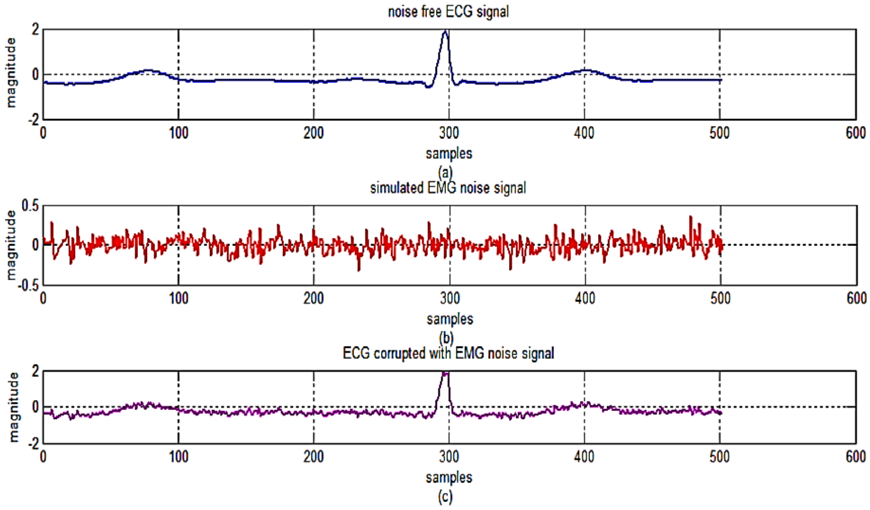

Fig III: a) Pure ECG data (b) Imitation EMG noise data (c) ECG tainted with EMG noise data

As we can analyze Figure IV, we can perceive the consequences of relating the ECG with EMG data exploitation to a 1X 3 MA strainer and 1 X 5 MA strainer.

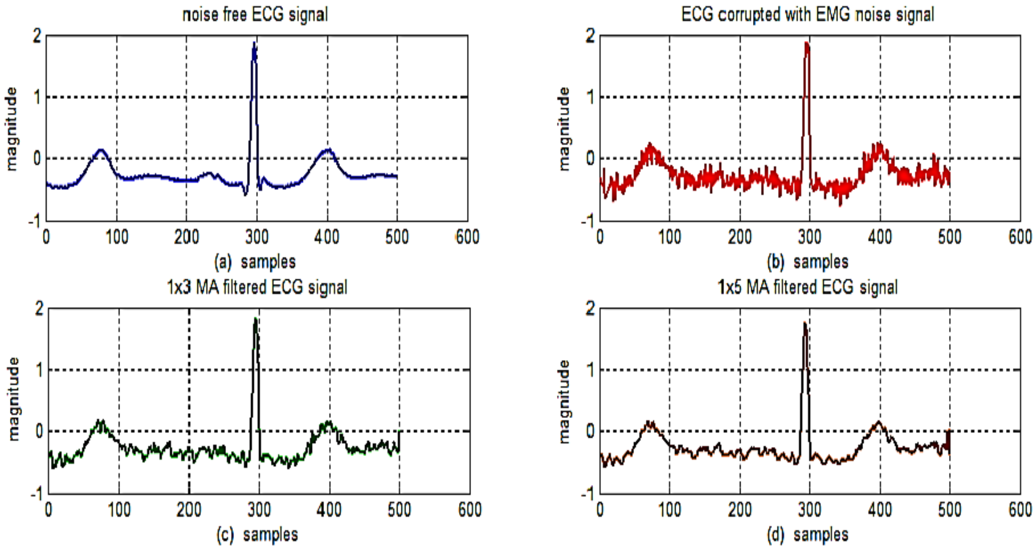

Fig IV: (a) Pure ECG signal (b) ECG tainted with EMG noisy data(c) Cleaned ECG signal using 1×3 MA strainer (d) Cleaned ECG signal using 1×5 MA strainer

We collect fast Fourier transforms (FFTs) of the signals in question so that we may analyze the performance of the filters in the frequency domain. The frequency spectra of the signals are presented in Figure V. When compared to the 1X3 filter, the 1X5 MA filter has been shown to greatly lower the amplitude of unwanted frequency components. This finding has been observed.

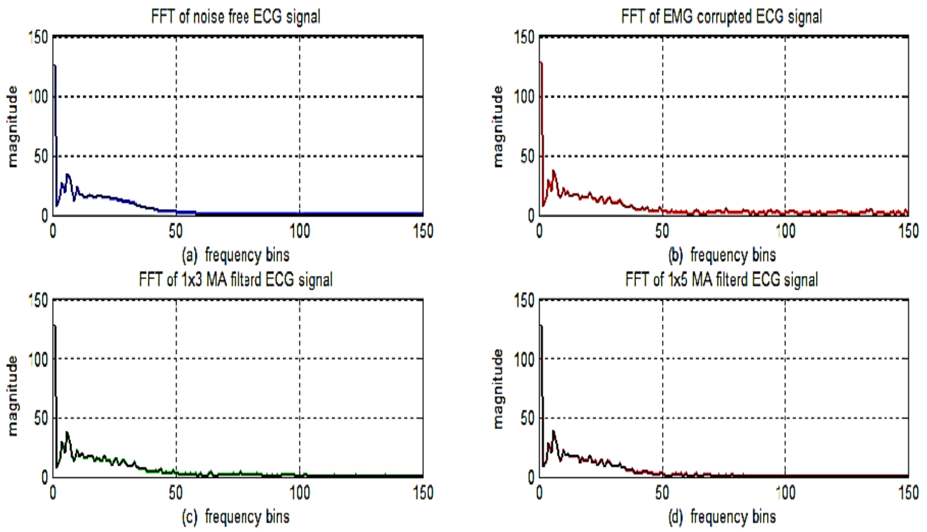

Fig V: (a) Frequency band of pure ECG data (b) Frequency band of EMG tainted ECG data (c) Frequency band of 1×3 MA cleaned ECG data (d) Frequency range of 1×5 MA cleaned ECG data

SNR, Mean Square Error (MSE), and the Smoothing Index can be used to justify the output performance of a 1X 3 and 1X 5 MA filter (SI). We have tabulated the results in the table I below.

Table I: Valuation considerations of 1×3 and 1×5 MA strainer.

	AWGN effected ECG signal	
	1×3 MA filter	**1×5 MA filter**
SNR	27.12	19.35
MSE	0.0075	0.091
SI	0.562	0.616
ASR	0.068	0.155

It has been noted that the FFT filter, despite the fact that it smooths the signal more effectively and offers a decent visual interpretation, offers metrics of a poor quality.

When it comes to reducing background noise, there are a number of methods that have been developed and compared. They include the Visu shrink, Global SURE shrink, Hybrid shrink, and Hybrid VS/WF methodology as shown in Table II. In each of these cases, db5 wavelet is employed in conjunction with either the Visu shrink, Global SURE shrink, or Hybrid shrink techniques. In the case of the Hybrid VS/WF approach, the experiment was run using two variants of the wavelet transform. The signal is represented compactly using Daubeches (db5) and symlet (sym6) wavelets. The sym6 filter bank is slightly larger than the db5 filter bank, allowing for the estimation of d N coefficients. De-noising methods are investigated for the simulated ECG signal with noise from an electromyograph and power line interference. Decomposing the noisy signal into three distinct layers allows us to isolate the coefficients of the approximation in which the noise terms reside. The specific coefficients are subjected to wavelet de-noising methods. The reconstructed signal is then obtained via an inverse wavelet transformation of the approximation coefficients and the adjusted detail coefficients.

Table II. Valuation constraints for filtering ECG tainted Signal.

Thresholding Methods	SNR	MSE	ASR	SI
Visu shrink	25.02	0.012	0.253	0.81
Gobal SURE shrink	24.34	0.012	0.245	0.81
Hybrid Shrink	28.44	0.008	0.218	0.87
Hybrid VS/WF	34.52	0.004	0.182	0.84

The peak amplitude of the QRS complex is maintained using the Hybrid VS/WF technique for EMG noise suppression, and the ECG signal may be visually interpreted better than with other methods.

Visu shrink approach is shown to have a low SI value but a high MSE compared to other methods. Because the Visu downsize technique uses a universal threshold with high value, noise and some legitimate signal coefficients are eliminated, making the results useful. This means the signal has been smoothed too much, which in turn causes a decline in goodness-of-fit. Whilst they do a better job of smoothing the signal, the global SURE shrink and hybrid shrink approaches do not provide the least MSE. The output waveforms accurately reflect the zigzagging nature of the Hybrid shrink method, despite the fact that its MSE is lower than those of the Visu shrink and Global Sure shrink. The Hybrid VS/WF method is able to circumvent these constraints. While the SI is slightly higher than with the Visu shrink method, a high SNR and low MSE are the results of using this technique. Spreading of the signal and poor performance result from using two wavelet functions with vastly different filter banks.

5. Conclusion:

Very significant properties (P-QRS-T) in ECG signals are extremely vulnerable to background noise. As there is background noise, the ECG signal is not as clear as it may be. At the preprocessing stage of ECG, it becomes the most difficult work to extract the original information from a signal and to eliminate the other sources of interference as doctors assess irregular changes in the P, QRS, and T waves to detect the various arrhythmias. In this study, we analyze the effectiveness of a proposed Hybrid VS/WF approach for reducing noise in electrocardiogram (ECG) signals across many domains. This work implements and evaluates a number of different filtering strategies across multiple domains in an effort to de-noise the ECG signal. While the 15 MA filter's effectiveness does come at the expense of a slight reduction in SNR, it is much more effective than the 13 MA filter at removing a large quantity of noise. While the FFT filter's performance is adequate for mitigating power line interference, its SNR is disappointingly low. Quality metrics are shown to be subpar when using MA filters or FFT filters. When compared to alternative shrinking techniques, such as Visu Shrink, Global Sure Shrink, and Hybrid Shrink, the suggested Hybrid VS/WF filter performs better. The experimental results demonstrate that the Hybrid VS/WF filter efficiently keeps the ECG signal shape while significantly decreasing the above discussed disturbances.

Conflict of Interests:

The authors declare that there is no conflict of interests regarding the publication of this paper.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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