Stationary wavelet transform based ECG signal denoising method [3] Paper Replication

First P. Vera, *Fellow, IEEE*, Second B. Author, and Third C. Author, Jr., *Member, IEEE*

***Abstract*—ECG or electrocardiogram signal are used in medicine tu diagnose cardiavasscular diseases. This is why obtaining a clean and clear signal is a top priority when performing this exam. Although given its nature the existing data are quite large, adding the non-stationary nature of the signal as an important variable to consider. This is why the purpose of this paper is to propose the stationary wavelets in addition to other methods used for comparison as a basis to evaluate their performance.**

***Index Terms*—ECG-Electrocardiogram, CVDs-cardiovascular disease, SNR - signal to noise ratio, PRD-percentage root mean square difference, MSE-root mean square error.**

I. Introduction

CARDIOVASCULAR disease (CVDs), refers to a group of disorders of the heart and blood vessels, including heart attacks, heart failure, and strokes. The main problem with analyzing an ECG signal is its nature as a non-stationary signal, which is why noise cleaning is handled differently. The heart's conduction system controls the generation and propagation of electrical signals that cause the heart muscle to contract and the heart to pump blood. This electrical activity is recorded by placing electrodes on the skin of the body. Given the nature of the medicine, the following noises occur.

- PowerLine Interference: It is a noise that is found in the frequency range of 50 and 60 Hz and is generally caused by the power line.
- Baseline Wandering:It is a low-frequency (0.15 up to 0.3 Hz) noise. This noise results from the patient inhaling and compels a baseline shifting of the ECG signals [1].
- Motion Artifacts: They are low-frequency noises that result from the displacement of electrodes placed on the skin and subject movement [3].
- Eletromyogram Noise: (created by muscles): Electromyogram noise generally occurs due to muscle contraction and relaxation other than cardiac muscles and lies typically in the frequency range of 5–500 Hz [3]

For this work we will focus only on eliminating noise PowerLine Interference.
For this case the Dataset will be used "MIT-BIH Arrhythmia Database"[4].

A. MIT-BIH Arrhythmia Database

The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Twenty-three recordings were chosen at random from a set of 4000 24-hour ambulatory ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample.
For this case and due to the demanding nature of the data in computing issues, only 10 people will be involved.

With which 3 comparison metrics will be used between the methods, SNR, MSE and PDR, as indicated in Fig.1.

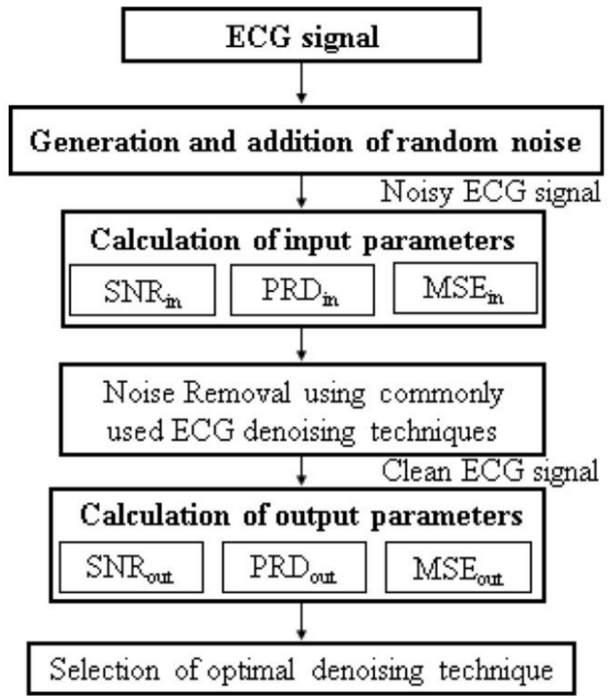

Fig. 1. Estructure of the proposed comparative method

II. Existing methods to evaluate denoising performance

This section examines various techniques employed for noise elimination in an ECG, as already proposed in the original paper [3]. We begin with two filters, a low-pass, and a high-pass filter. We then explore the Discrete Wavelet Transform (DWT) as an initial step to investigate a characteristic of adaptive threshold. Subsequently, we delve into the Decomposition Technique in empirical mode, a Fourier variation, and finally, the proposed method, which is the Stationary Wavelet Transform (SWT).
In the development, we will proceed to explain in detail each technique to be used:

A. Lowpass Filter and Highpass Filter

Lowpass filter and high-pass filter with a cutoff frequency of 0.5 Hz–40 Hz are used in the present work as the energy of the ECG signal (P-wave,QRS complex, and T-wave) lie in 0.5 Hz–40 Hz frequency range. The difference equation of the low-pass filter and the high-pass filter used in the present work, indicated by the author of the original paper [3], are:

$$H1(z) = \frac{0.8576 - 0.032z^{-1} + 0.8629z^{-2} - 0.0811z^{-3}}{1 - 1.2096z^{-1} + 0.2644z^{-2} - 0.0144z^{-3}} \tag{1}$$

$$H2(z) = \frac{-0.5034 + 1.9441z^{-1} - 1.9441z^{-2} + 0.5034z^{-3}}{1 - 1.1737z^{-1} + 0.2982z^{-2} + 0.0245z^{-3}} \tag{2}$$

B. Discrete Wavelet Transform

In DWT, the ECG signal is subsampled at each level, and simultaneously, the detail coefficients are subjected to denoising thresholds. Some thresholding schemes are hard threshold, adaptive threshold, soft threshold, sure shrink threshold, and universal threshold. Among the above thresholding techniques, adaptive thresh-olding is most suitable for ECG signal denoising. After eliminating noise, finally, the inverse of DWT is performed to reconstruct the denoised ECG signal. In the present work biorthogonal 3.1 wavelet transform with adaptive thresholding is used to decompose the noisy ECG signal.

C. Empirical Mode Decomposition Technique

EMD is employed on the noisy ECG signal. In the preprocessing stage, the data is normalized. Then, EMD decomposes a non-stationary time series into a finite number of intrinsic mode functions, which are monocomponent non-stationary signals.

D. Fourier Decomposition Method

A noisy ECG signal is decomposed into a set of monocomponent non-stationary signals by dividing the signal's complete bandwidth into an equal number of frequency bands. These monocomponent non-stationary signal frequency bands are known as Fourier intrinsic band functions (FIBFs). The maximum frequency of an ECG signal is calculated by dividing the sampling frequency by two. The maximum frequency is used to determine the cutoff frequency of each FIBF. FIBF should have zero mean function, which means the segmented ECG signal provides a zero DC level shift. The segmented ECG signal contains low and high-frequency components only. After determining FIBFs, various parameters like SNR, PRD, and MSE of each FIBF are competed. Eight FIBFs are extracted from the noisy ECG signal, and the output of the 8th FIBF is the denoised ECG signal.

Highlight that the Components meet certain conditions[5],[3]:

- The FIBFs are zero mean functions, that is $\int_a^b y_i(t)\, dt = 0, \forall i$
- The FIBFs are orthogonal functions, that is $\int_a^b y_i(t) y_j(t)\, dt = 0, j \neq i$
- FIBFs show analytical representation with instantaneous frequency and instantaneous amplitude, which is represented by $\omega_i(t) = \frac{d}{dt}\psi_i(t) \geq 0$ and $a_i(t) \geq 0$

E. Stationary Wavelet Transform

After the pre-processing, the input ECG signal is subjected to a series of a lowpass filter and highpass filter to reject the frequency band as per the Nyquist criterion. This method does not perform any subsampling or decimation. Hence, the length of both the signals produced from the lowpass filter and highpass filter remains the same. At each level, the signal is decomposed into detailed coefficients and approximate coefficients. The approximate coefficients are outputs of lowpass filters (hi [n]), and detail coefficients are the outputs of highpass filters (gi [n]). This process continues up to "n" decomposition levels

III. Comparison with the original Paper

Since this is a comparative paper, many of the methods, ideas and paths used to solve the original problem are based on the logic of the original paper [3], The big difference for this case is the implementation of all the methods in matlab code. The generation of random noise is based on a 60 Hz sine with a random amplitude ranging between 0 and 1/5 mV, which is added to the original signal. Referring to the comparison parameters, in the SNR method, it will be calculated as the difference between the SNR of the output signal and the SNR of the input signal. For the MSE method, the classical approach will be followed, but it is crucial to highlight that PDR will be used according to the standard implementation in MATLAB [2]. This procedure has been meticulously reviewed by an expert in ECG signal analysis.

IV. Results

Below are three tables containing the metrics for each method employed for each of the 10 individuals in the dataset.

TABLE I
SNR for each method used for each of the 10 individuals in the dataset.

ECG Record	Input	EMD	LPF	HPF	FDM	DWT	SWT
100	3.9459	0.2453	2.0147	5.3587	1.2920	2.7021	-4.2095
101	0.4492	0.5144	3.2102	6.6537	5.6097	1.3325	-0.6941
102	0.2065	0.2086	1.2050	7.3702	1.8981	1.5306	-0.4746
103	-0.3863	0.0942	3.5411	5.5073	4.3551	1.0191	0.0131
104	-0.4078	-5.8325	2.3087	-2.5950	2.1425	0.2387	0.2871
105	-0.3512	0.0246	2.2113	4.9846	1.3178	0.2558	-0.1416
106	-0.1597	0.0878	4.2515	2.6827	6.8921	1.4119	-0.1366
107	-0.062	-0.0104	0.8948	-4.1908	0.5438	0.0662	-0.0767
108	-3.0034	-0.0057	4.6496	7.3427	6.1881	1.2539	2.3566
109	-0.303	0.0404	1.5869	0.7608	2.1152	0.0738	-0.1354

In the SNR method (TABLE I), the objective is to maximize the numerical value, striving for an optimal signal-to-noise ratio. Conversely, for the MSE method (TABLE II), the goal is to minimize the mean squared error, seeking precision in the analysis. Within the PDR method(TABLE III), the 'Input' column serves to elucidate the initial relationship between the noise-free signal and the noisy signal. This preliminary insight allows for subsequent comparisons between the noisy signal and the signal purified through the application of the method.

TABLE II
MSE FOR EACH METHOD USED FOR EACH OF THE 10 INDIVIDUALS IN THE DATASET.

ECG Record	**Input**	**EMD**	**LPF**	**HPF**	**FDM**	**DWT**	**SWT**
100	0.0067	0.1175	55.1972	0.1487	0.0250	0.0209	0.0058
101	0.0067	0.0720	42.1725	0.1216	0.0380	0.0238	0.0067
102	0.0067	0.0561	35.5106	0.1053	0.0188	0.0212	0.0065
103	0.0067	0.0522	40.1125	0.1248	0.0636	0.0312	0.0075
104	0.0067	0.0617	44.7471	0.1304	0.0252	0.0202	0.0077
105	0.0067	0.0379	44.8299	0.1381	0.0233	0.0169	0.0038
106	0.0067	0.0360	39.4231	0.1231	0.0803	0.0337	0.0077
107	0.0067	0.1069	255.0872	0.6989	0.0642	0.0247	0.0085
108	0.0067	0.0790	36.9146	0.1065	0.0154	0.0165	0.0037
109	0.0067	0.0927	85.3786	0.2431	0.0429	0.0163	0.0039

TABLE III
PDR FOR EACH METHOD USED FOR EACH OF THE 10 INDIVIDUALS IN THE DATASET.

ECG Record	**Input**	**EMD**	**LPF**	**HPF**	**FDM**	**DWT**	**SWT**
100	20.1532	178.7702	447.1548	330.3665	43.7138	43.5472	23.6008
101	61.2862	115.4297	449.5286	284.2933	64.3123	30.4563	43.6973
102	46.2707	115.3896	447.0584	397.0496	47418	62.8078	60.7647
103	159.4117	69414	459.9491	183.3363	80.6313	121.4385	153.1188
104	92.2528	92.3733	448395	356.6589	48.4534	103.447	99.0456
105	120.0402	59224	453.3132	280.2853	42729	104.146	135.6715
106	187.0114	53.5835	461.2294	180.8291	99.1898	123.3026	188.099
107	168.9218	39.9348	450.0042	364478	30391	172.9604	169.715
108	92.7225	172.6518	445.6395	533429	42.4942	92.7935	94.255
109	45.2998	75.2036	450.4737	342.8074	44.3823	53.0812	15.4656

V. CONCLUSION

Although it is early to draw conclusions, the SWT method appears quite promising.

.

REFERENCES

[1] Selcan Kaplan Berkaya, Alper Kursat Uysal, Efnan Sora Gunal, Semih Ergin, Serkan Gunal, and M Bilginer Gulmezoglu. A survey on ecg analysis. *Biomedical Signal Processing and Control*, 43:216–235, 2018.

[2] Said BOUREZG. The percent root difference (prd): Versión 1.0, 2023.

[3] Ashish Kumar, Harshit Tomar, Virender Kumar Mehla, Rama Komaragiri, and Manjeet Kumar. Stationary wavelet transform based ecg signal denoising method. *ISA transactions*, 114:251–262, 2021.

[4] George B Moody and Roger G Mark. The impact of the mit-bih arrhythmia database. *IEEE engineering in medicine and biology magazine*, 20(3):45–50, 2001.

[5] Pushpendra Singh, Shiv Dutt Joshi, Rakesh Kumar Patney, and Kaushik Saha. The fourier decomposition method for nonlinear and non-stationary time series analysis. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 473(2199):20160871, 2017.