

# Comprehensive Time-Frequency Analysis of Noisy ECG Signals – A Review

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## Abstract

This article is based on a comparison of various time-frequency analysis techniques for reducing noise in an ECG signal. Noise continuously degrades the quality of the ECG signal. Due to the ECG signal's time-varying nature, ECG noise reduction is extremely challenging. The diagnosis of heart disorders requires an ECG signal of high quality. This study presents a survey of several techniques and noise types that can distort the ECG signal. The signal is denoised using effective denoising techniques such as the Wavelet Transform, Empirical Mode Decomposition (EMD), Empirical Wavelet Transform (EWT), Short Time Fourier Transform (STFT), Ensemble and Empirical Mode Decomposition (EEMD). Compared to previous de-noising approaches, the EWT de-noising methodology is more effective and has a lower computing complexity.

## Keywords

ECG, Denoising, EMD, EEMD, EWT

## Imprint

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## 1. Introduction

An illustration of how the human heart functions is provided by the electrocardiogram (ECG). ECG signals typically vary from 0.05 to 100 Hz in frequency and 1 to 10 mV in dynamic range. The electrocardiogram (ECG) is only a voltmeter that attaches up to 12 distinct leads (electrodes) to the chest, arms, and legs of the pa-

tient. A distinct waveform with the same shape will be recorded by each sensor separately. The letters P, Q, R, S, and T are used to identify the five peaks and valleys that make up the ECG signal. Figure 1 illustrates the ECG signal's additional U wave, which has a very low amplitude or is absent even more frequently. The ECG, which also shows that blood is flowing to the heart muscle, can quantify the heartbeat's rhythm and tempo. ECG is a signal that is not stationary and is influenced by different disturbances, including interference from power lines, baseline drift, electrode contact, and EMG during acquisition and transmission of signal. One of the applications of time-frequency analysis is denoising [1-2]. Various denoising strategies are covered in this paper along with analyses of various noises. The following sections are structured as follows. Section 2 contains various disturbances in the ECG signals. Section 3 presents several ECG signal denoising methods, and conclusion & future scope are presented in section 4.

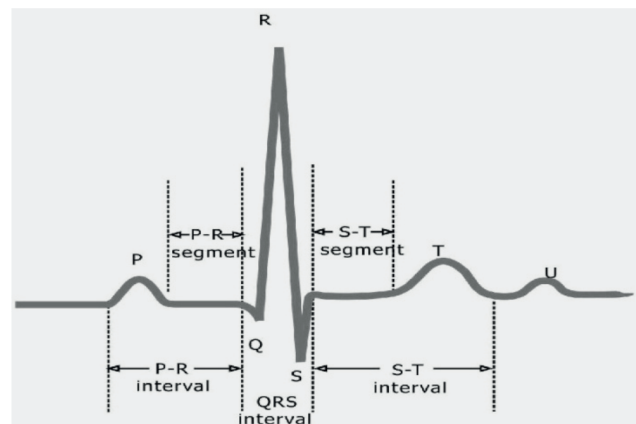


Figure 1 Normal ECG waveform

## 2. ECG signal Interference

Different types of disturbances can contaminate the ECG signal, including electrosurgical noise, instrumentation noise produced by electronic instruments, motion artefacts, muscle contraction, base line drift, and interference from power lines.

### Power line interference

Electromagnetic interference from power lines is the main cause of the interference. Electrical fields produced by surrounding devices, stray alternating current fields caused by wire loops, and improper grounding of either the patient or the ECG machine. The ECG machine's input circuits are subjected to 50 Hz impulses from the electrical apparatus.

## Baseline Wander

The ECG signal contains a low-frequency noise element called baseline wander. The main causes of this include breathing and movement of the body. Frequency of baseline wander is higher than 1Hz. The identification and analysis of the peak are complicated by this Baseline drift.

## Noise from Electrode Contact

When the electrode loses touch with the skin, electrode contact noise results, essentially separating the individual from the measurement apparatus. The duration of this type of noise is 1second.

## Motion Artifacts

Patient movement will result in variations in electrode skin impedance during the recording of the ECG. The magnitude of this noise is 500% greater than the ECG's peak-to-peak amplitude and lasts for 100-500 milliseconds.

## Instrumentation Noise

Electrical devices make this type of noise as part of the ECG acquisition system. Along with the electrical apparatus used for ECG capture, auxiliary sources such electrode probes, ADC converters and power cables also play a role.

## 3. Denoising techniques

### Fourier Transform:

A signal is divided into constituent sinusoids with various frequencies using the Fourier analysis. Fourier analysis can also be thought of as a mathematical method for changing the perspective on the signal from one that is time-based to one that is frequency-based. When Fourier analysis is transformed into a frequency domain, time information is lost. When examining a signal's Fourier form, one cannot precisely determine when a specific occurrence happened.

### Short-Time Fourier Transform:

Time-frequency analysis is the most typical usage of Short-Time Fourier Transform (STFT). By using STFT, a signal is converted into a two-dimensional frequency and time function. A fixed-width window function is chosen in STFT, and this window then slides across the entire signal. The signal inside the window is constant in this instance [3]. The signal

$x(t)$ 's inner product is then calculated inside the window. The disadvantage is that, when selecting a specific size window, the same size window is applied for all frequencies. The windowing of a signal in the Short Time Fourier transform is explained in Figure 2.

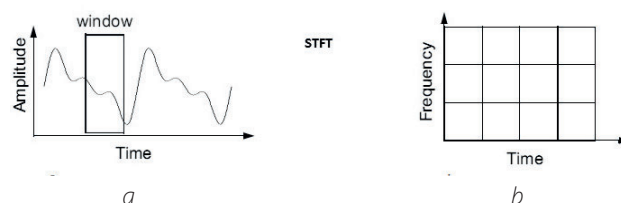


Figure 2 (a) Signal Windowing (b) STFT Time Frequency resolution

Good time resolution is provided with a small window, but weak frequency resolution, in contrast to a wide window. Using the multi-resolution analysis-based wavelet transform, the STFT's resolution problem is resolved.

## Wavelet Transform

Similar to the STFT, Not all spectral components are resolved evenly. High frequencies have strong time resolution and poor frequency resolution when utilizing a multi-resolution analysis, whereas low frequencies have good frequency resolution and bad time resolution. This idea is crucial for the signal, which consists primarily of low frequency components and briefly of relatively components of high frequency in the middle. Figure 3 illustrates how to evaluate time and frequency resolutions when using the wavelet transform approach.

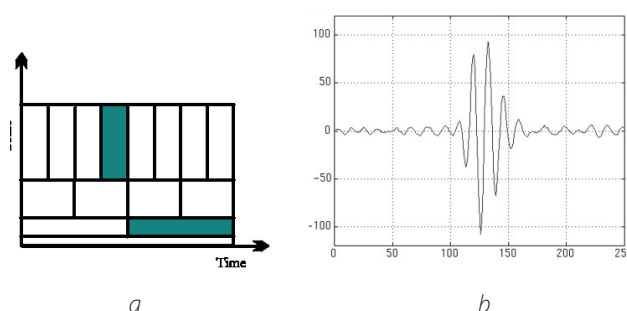


Figure 3 a) Resolution of Time and Frequency via Wavelet Transform. b) Analysis of Multi-resolution

Signals can be analyzed using the wavelet transform as a linear combination of the mother wavelet and the sum of the wavelet coefficients, which does not add any extra information to the original signal [4-5]. However, signal denoising greatly depends on the choice of an appropriate wavelet function and thresholding technique.

## Empirical Mode Decomposition

Huang. established a Technique called Empirical Mode Decomposition (EMD), an adaptive T-F analysis approach for breaking down a non-stationary and nonlinear signal into a predetermined number frequency components. In order to build a “time-frequency-energy” representation of the data based on the generated Intrinsic Mode Functions (IMFs) that the EMD creates from the data, there is a need for Hilbert spectral analysis. The time series is divided into a superposition of components with clearly specified instantaneous frequencies using IMFs.

By using sifting process, A group of intrinsic mode functions are created from the original signal [6-7]. The frequency of the IMF components that are separated first is highest, and the frequency of those that are separated last is lowest. The final element is having a single extreme point. Any two IMF are independent, there is some symmetry between the top and lower envelope curves and the time axis. The formula for a noisy signal,  $x(t)$ , is  $x(t) = y(t) + n(t)$ , where the noise-free signal is denoted by  $y(t)$  and the additive noise is denoted by  $n(t)$ . An IMF is a function that meets the two requirements: zero-crossings and extrema are identical in number or differ by one, and the second requirement is that the upper and lower envelopes’ average value must always be zero across the whole data set [8]. From higher-frequency bands (initial IMFs) to lower-frequency bands (last IMFs), each IMF in this decomposition represents a specific frequency band of the input signal  $x$  [9].

### Sifting process

The description of the sifting process as follows:

- The original signal’s local maxima and minima points are first identified.
- The lower envelope and upper envelope are formed from the respective local minima and local maxima using the cubic spline method.
- The mean value  $m_1$  is calculated by averaging the upper and lower envelopes. The first intrinsic mode function component  $h_1(t)$  is then created by subtracting this mean value  $m_1$  from the original signal  $x(t)$ .

$$h_1(t) = x(t) - m_1 \quad (1)$$

- The sifting procedure described in the preceding steps is repeated on the current difference signal ( $h_1(t)$ ) if this difference  $h_1(t)$  is not an IMF.

$$h_{11}(t) = h_1(t) - m_{11} \quad (2)$$

The average of  $h_1$ ’s upper and lower envelope values is  $m_{11}$ .

If after  $k^{\text{th}}$  term  $h_{1k}$  becomes an IMF, *i.e.*,

$$h_{1k}(t) = h_{1(k-1)}(t) - m_{1k} \quad (3)$$

The first residual component,  $r_1$ , is produced from the original signal after the IMF1 component has been removed.

$$r_1(t) = x(t) - c_1(t) \quad (4)$$

- The next IMF is then calculated using the residual component  $r_1(t)$ , which is saved as new data and put through the same procedure as before.

$$r_2(t) = r_1(t) - c_2(t) \quad (5)$$

$$r_N(t) = r_{(N-1)}(t) - c_N(t) \quad (6)$$

- as long as the final residual component doesn’t become a monotone function, the procedure is repeated until no more IMF can be recovered.
- It is possible to obtain the EMD of the original signal and to express it as

$$x(t) = \sum_{n=1}^N C_n(t) + r_n(t) \quad (7)$$

The method of breaking down the ECG signal into IMFs is shown by the tree in Figure 4.

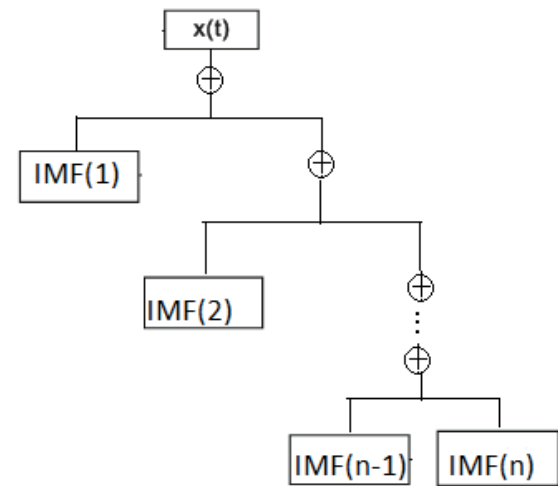


Figure 4 Decomposing a signal into IMFs

Mode mixing is defined as the regular occurrence of an IMF that either consists of signals with diverse scales or with the same scale but appearing in various IMFs and stop criteria are significant downsides of this approach [10-14]. EMD is a highly effective technique. However, a weak grasp of mathematics. The process of EMD is slow and complex.

## Ensemble Empirical Mode Decomposition

The data analysis technique known as Ensemble Empirical Mode Decomposition (EEMD) significantly outperforms the EMD technique. This approach has been suggested as a solution to the mode mixing issue with the EMD technique. By repeatedly performing the decomposition operations, the EMD approach enables the delivery of all solutions that yield the genuine IMF.

The ensemble mean is a popular method for increasing accuracy when data from various observations with varied levels of noise are combined. It is presumptively true that the white noise applied to the single data set corresponds to the probable random noise that would be present during the measurement process. The EEMD technique involves the following steps:

Boost the signal being investigated in Step 1 with white noise, with a predetermined noise amplitude.

Step 2: Decompose the newly generated signal using the EMD approach.

Step 3: Re-do the signal decomposition described above using different white noise, with the extra white noise's amplitude fixed.

Step 4: As the last step, determine the ensemble means of the decomposition outcomes.

A residue and a small number of intrinsic mode functions (IMFs) are created from the signal's decomposition.

When using this EEMD approach, the extra noise's amplitude and number must be chosen. In addition, compared to the EMD, the computation time is relatively long.

## Empirical Wavelet Transform:

Empirical Wavelet Transform (EWT) is a brand-new technique for breaking down a signal into various modes. This approach's lack of theory is its primary flaw, despite the fact that its versatility appears to be advantageous for many applications. To extract the many modes of a signal, it is essential to build an efficient wavelet filter bank. [15-16].

The EWT approach has two key components: (i) segmenting the signal's spectrum; and (ii) Building the empirical wavelets and processing each segment of the signal with them.

## Process of EWT

Step 1: Proceed with an ECG signal.

Step 2: Apply certain Noise and consider this as the input signal.

Step 3: Using the Fourier Transform, determine the signal's spectrum.

Step 4: Find out all the local maxima's and all mid points between adjacent local maxima's.

Step 5: To segment the spectrum, first find the boundaries.

Step 6: Create empirical wavelets, then break the signal down into its component parts.

The calculation of Mean Square Error is shown in the equation 8.

$$MCE = \frac{1}{N} \sum_{n=1}^N \left( x(n) - \overline{x(n)} \right)^2 \quad (8)$$

Mean Square Error (MSE) is displayed in Table 1 at different SNR levels for different denoising techniques.

Table 1

Comparison of MSE achieved using various denoising methods

SNR (dB)	MSE				
	STFT	DWT	EMD	EEMD	EWT
-10	0.388	0.1046	0.0928	0.0749	0.02
-5	0.253	0.0389	0.0291	0.0274	0.025
0	0.024	0.0138	0.0086	0.0080	0.0024
5	0.009	0.0071	0.0044	0.0042	0.0023
10	0.0392	0.0038	0.0033	0.003	0.0022

A new technique called EWT works similarly to EMD [17]. The reference paper [18] described how EWT is utilized to get rid of power line interference and baseline wander interference, which impact the ECG signal since EMD is a lengthy and complicated operation. EWT has two limitations: the need to define the number of modes and improper spectrum segmentation. Integrated approaches can be suggested [19-20] in order to prevent the incorrect segmentation in the EWT method.

## 4. Conclusion and future scope

This survey provides a comparison of signal denoising methods conducted by various researchers. Fourier transform is inappropriate for an ECG signal because it is a non-stationary signal. Although the Wavelet Transform is a very valuable tool for signal analysis, however since the same fundamental wavelet is used for all of the data in the signal, certain high frequency noise cannot be completely eliminated from the ECG signal. An adaptive time-frequency data processing method known as EMD can overcome the non-adaptiveness of the wavelet transform approach by eliminating the high



frequency noise. EWT gives smallest MSE than the other techniques and computation time is significantly reduced. In order to prevent the EWT method's incorrect segmentation, integrated methods can be proposed. The combination of two techniques suggests that it will be more effective to examine the ECG signal.

## References

1. Cohen, Leon. Time-frequency signal analysis. Ed. Englewood Cliffs, NJ: Prentice Hall 1995.
2. Tanusree Ghosh, Debnath Bhattacharyya, Samir Kumar Bandyopadhyay, Tai-hoon Kim. A Review on Different Techniques to De-noise a Signal. *International Journal of Control and Automation*. 2014; 7(3): 349-358.
3. Mishra, A., Sahu, S.S., Sharma, R. et al. Denoising of Electrocardiogram Signal Using S-Transform Based Time-Frequency Filtering Approach. *Arab J Sci Eng*. 2021; 46: 9515-9525.
4. H.D.Praveena, C.Subhas, K. Rama Naidu, Detection of Epileptic Seizure based on ReliefF Algorithm and Multi Support Vector Machine. *Advances in Intelligent Systems and Computing (AISC) springer series*. 2020; 1040: 13-28.
5. M. Alam, M. I. Islam and M. R. Amin. Performance Comparison of STFT, WT, LMS and RLS Adaptive Algorithms in Denoising of Speech Signal. *IACSIT International Journal of Engineering and Technology*. 2011; 3(3): 235- 238.
6. Huang, Norden E., et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. *Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences*. 1998; 454(1971): 903-995.
7. H.D.Praveena, C.Subhas, K.Rama Naidu., Classification and Discrimination of Focal and Non-focal EEG Signals using Hybrid Features and Support Vector Machine. *International Journal of Advanced Intelligence Paradigms*. 2021; 18(3): 417-437.
8. B.Pradeep Kumar, S. Balambigai. A Survey on ECG Denoising Techniques. *Bonfring International Journal of Advances in Image Processing*. 2012; 2(1): 285-290.
9. A. Chacko and S. Ari. Denoising of ECG signals using Empirical Mode Decomposition based technique. *IEEE-International Conference on Advances in Engineering, Science and Management (ICAESM - 2012)*. 2012; 6-9.
10. Maveria Mazhar Butt<sup>1</sup>, Usman Akram<sup>2</sup>, Shoab A. Khan. Denoising Practices for Electrocardiographic (ECG) Signals: A Survey. *International Conference on Computer, Communication and Control Technology*. 2015; 264-268.
11. Praveena H D, K.Sudha, P.Geetha. Support Vector Machine Based Melanoma Skin Cancer Detection. *Journal of University of Shanghai for Science and Technology*. 2020; 22(11):1075-1081.
12. Sarang L Joshi, Rambabu A.Vatti, Rupali V.Tornekar. A Survey on ECG Signal Denoising Techniques. *International Conference on Communication Systems and Network Technologies (IEEE)*. 2013; 60-63.
13. Praveena HD, K.Sudha, V.Navya, Ch.V.M.S. Pavan Kumar. High Density Impulse Noise Removal Using Trimmed Global Mean. *Journal of Advanced Research in Dynamical and Control Systems*. 2017; 9(14): 779-788.
14. H.D.Praveena, C.Subhas, K.Rama Naidu. iEEG based Epileptic Seizure Detection using Reconstruction Independent Component Analysis and Long Short-Term Memory Network. *International Journal of Computers, Communications and Control*. 2021; 16(5): 1-10.
15. Omkar Singh and Ramesh Kumar Sunkaria, Powerline interference reduction in ECG signals using empirical wavelet transform and adaptive filtering. *Journal of Medical Engineering Technology*. 2015; 60-68.
16. Omkar Singh and Ramesh Kumar Sunkaria, ECG signal denoising via empirical wavelet transform. *Australasian Physical & Engineering Sciences in Medicine*. 2016; 1-11.
17. H. D. Praveena, C. Subhas and K. Praveen. ECG Signal De-noising by using Empirical Wavelet Transform and Extended Kalman Filter. *International Journal of Pure and Applied Mathematics*. 2018; 120(6): 11983-11996.
18. M. Kedadouche, M. Thomas, A. Tahan. A Comparative study between Empirical Wavelet Transform and Empirical Mode Decomposition Methods: Application to bearing defect diagnosis. *Mechanical Systems and Signal Processing*. 2016; 81(15): 88-107.
19. Morasa, Balaji, and Padmaja Nimmagadda. Low Power Residue Number System Using Lookup Table Decomposition and Finite State Machine Based Post Computation. *Indonesian Journal of Electrical Engineering and Computer Science*. 2022; 6(1): 127-34.
20. Yeldos A. Altay, Pavel A. Kulagin. Evaluation of a damping coefficient influence made by notch filters on efficiency of ECG signals processing. *Cardiometry*. 2021;(19):20-37.