A COMPARATIVE STUDY OF CONVENTIONAL AND TRANSFORM DOMAIN DENOISING METHODS OF ECG SIGNAL

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Abstract: The Electrocardiogram (ECG) is a vital non-invasive tool for diagnosing cardiovascular diseases. However, during acquisition and transmission, ECG signals are often corrupted by various types of noise and artifacts, which can obscure critical morphological features and lead to misdiagnosis. This study systematically categorizes the primary sources of noise in ECG signals and provides a comparative analysis of conventional and transform domain denoising techniques, discussing their applications, advantages, and limitations.

Index Terms: ECG denoising, adaptive filters, digital filters, transform-domain denoising, wavelet transform

I. INTRODUCTION

Electrocardiography (ECG) is known as the measurement of the electrical activity of the human heart. For screening and diagnosis of many diseases, ECG is essential [1]. Figure 1 shows the original ECG signal waveform, downloaded from the MIT-BIH Arrhythmia database [2] of the PhysioNet [3] and plotted using MATLAB.

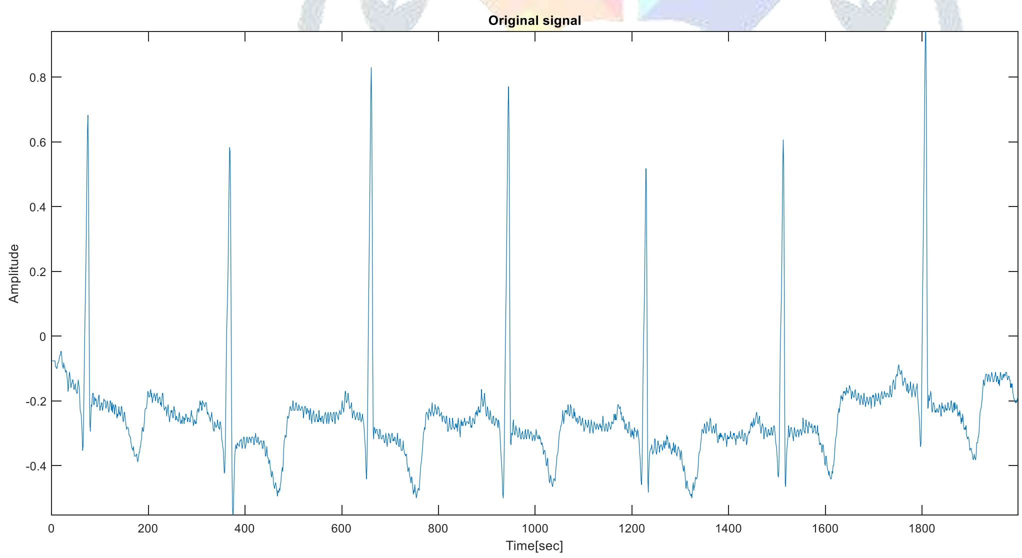


Figure 1: Electrocardiography (ECG) signal waveform

The ECG visually displays the heart's electrical activity, highlighting key components such as the P-wave, QRS complex, and T-wave, which are vital for accurate diagnosis. One cycle of a labeled ECG is shown in Figure 2. The amplitude of these waves is very small (measured in millivolts). The ECG signal is particularly vulnerable to interference from both biological and external sources. Therefore, effective denoising is a crucial step in preprocessing any automated ECG analysis system, as it helps preserve the diagnostic quality of the signal.

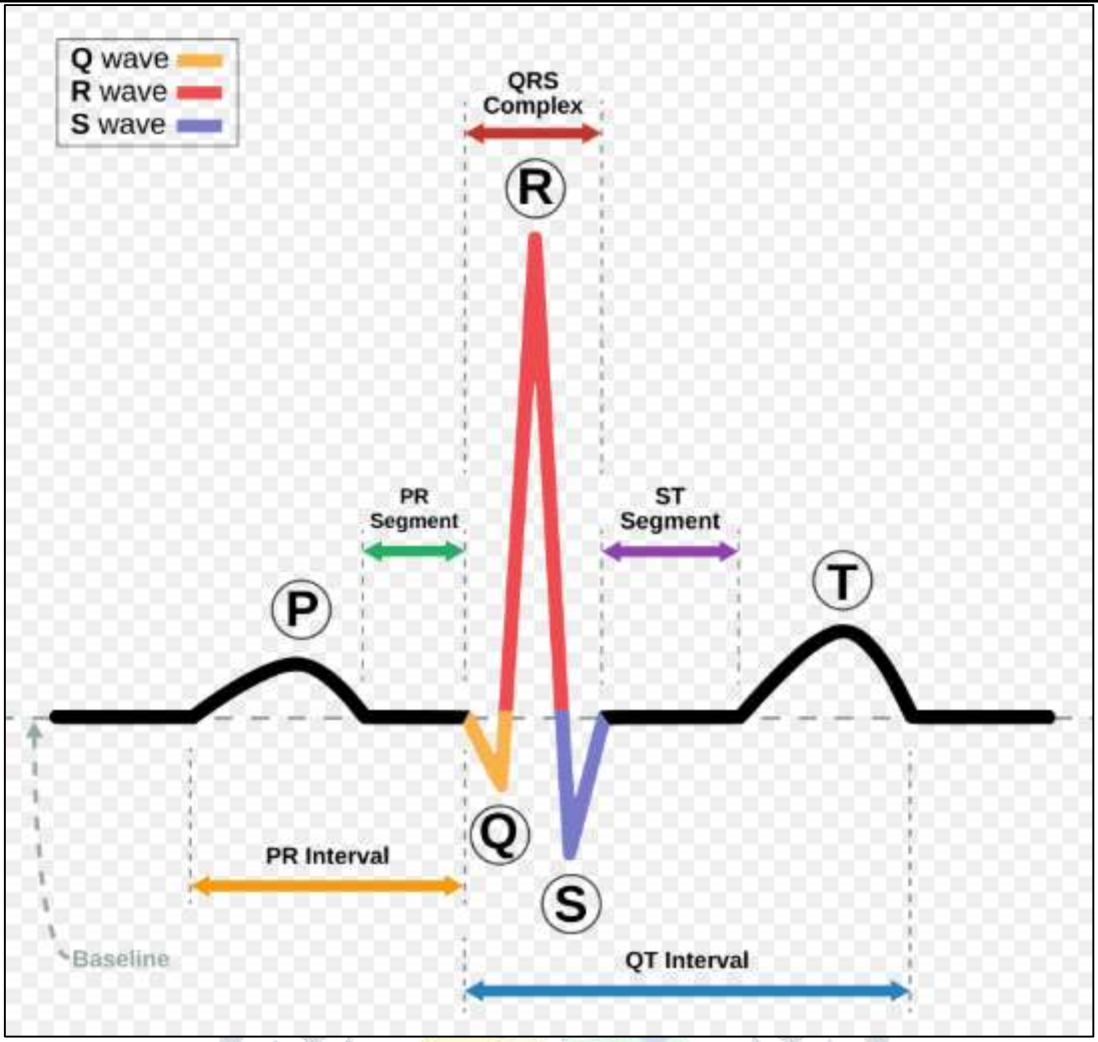


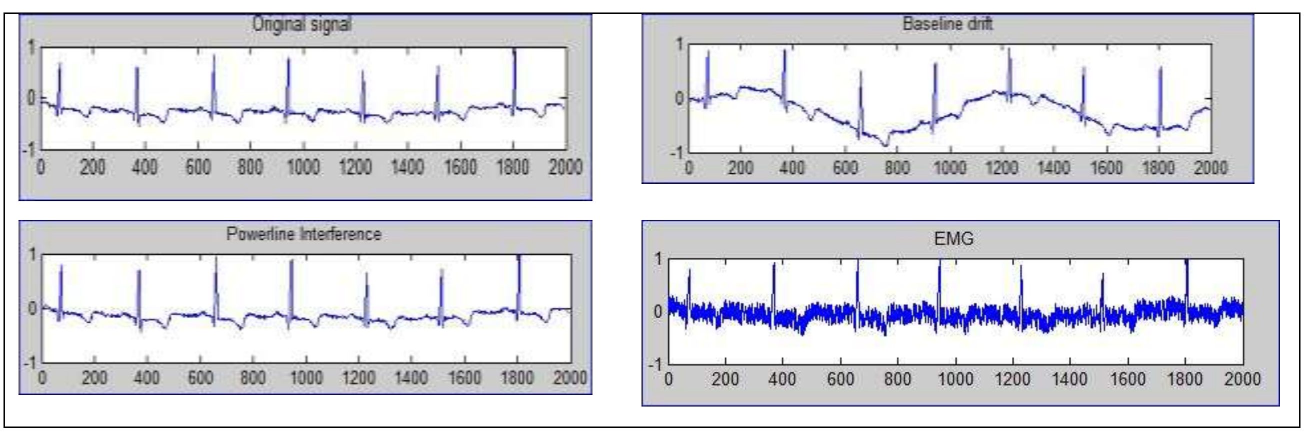
Figure 2: A labeled ECG wave (picture source: Wikipedia)

However, ECG signals are often affected by various types of noise. These noise sources can be categorized into two main groups: instrumental and external noise, as well as physiological noise originating from the patient's body [4]. Table 1 below lists these noise types along with their sources, characteristics, and impacts, and Figure 3 displays a plot of a noisy ECG signal corrupted by different kinds of noise and a combined noisy signal in the bottom figure.

As mentioned above, the integrity of the ECG waveform is vital for detecting variations in heart activity, highlighting the necessity of analyzing ECG parameters free from noise. Conventional filters may not adequately eliminate these noise elements, necessitating the use of specialized methods for denoising ECG signals. In this context, this study systematically categorizes the primary sources of noise in ECG signals and provides a comparative analysis of classical and modern denoising techniques, evaluating their performance, advantages, and limitations. Each method offers different advantages and performance characteristics, which are critical for improving the clarity and accuracy of ECG signal analysis.

Table 1: Primary sources of ECG noise

Instrumental and External Noise		**Physiological Noise (from the Patient's Body)**	
Power Line Interference (50/60 Hz)	○ **Source:** Electromagnetic interference from mains power. ○ **Characteristics:** Narrow-band, sinusoidal noise at 50 Hz or 60 Hz and its harmonics. ○ **Impact:** Obscures the ST segment and can distort the baseline.	**Baseline Wander**	○ **Source:** Patient's respiration and body movements. ○ **Characteristics:** Very low-frequency (typically 0.15 to 0.3 Hz), slow-varying drift of the isoelectric line. ○ **Impact:** Makes it difficult to analyze the ST segment and measure amplitudes accurately.
• **Electrode Motion Artifact**	○ **Source:** Changes in the skin-electrode impedance due to movement. ○ **Characteristics:** Low-frequency (typically < 1 Hz), high-amplitude, non-stationary, and erratic. ○ **Impact:** Can severely distort the baseline and mimic pathological conditions like ischemia.	**Electromyogram (EMG) Noise**	○ **Source:** Electrical activity from skeletal muscles. ○ **Characteristics:** Broadband, random, high-frequency (up to 10 kHz) noise that resembles white Gaussian noise. ○ **Impact:** Blurs the boundaries of the P and T waves and adds high-frequency components to the QRS complex.
Electrode Contact Noise	○ **Source:** Poor contact between the electrode and the skin. ○ **Characteristics:** Sudden, large-amplitude spikes or signal dropouts.	**Electroencephalogram (EEG) / Other Bio-electric Signals**	○ **Source:** Interference from other electrical activities in the body.



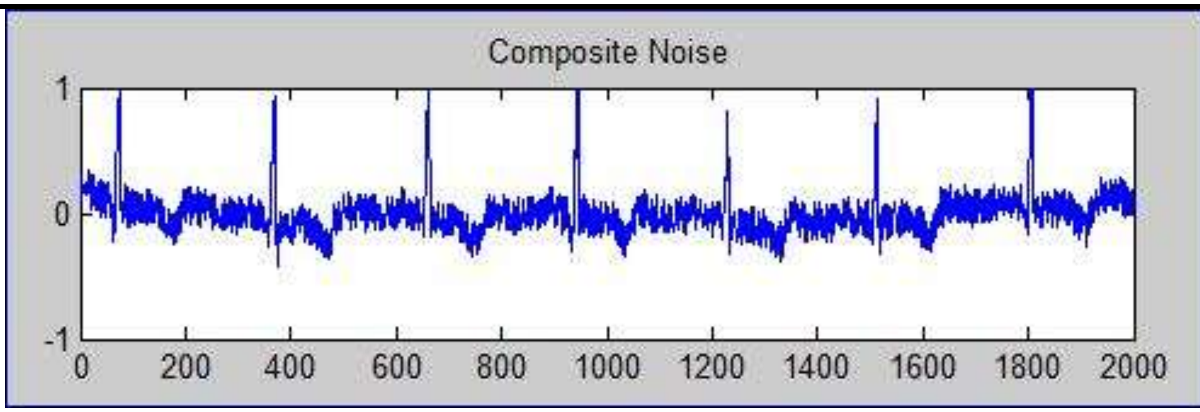


Figure 3: Plot of original ECG signal (Top left) corrupted by various kinds of noise such as baseline drift, powerline interference, EMG and composite noise (bottom)

II. ECG DENOISING METHODS

Denoising methods aim to suppress noise while preserving the crucial morphological features of the ECG. They can be categorized as conventional methods and transform domain methods. The conventional methods include digital filters and adaptive filters. Digital filetres include finite inpulse response filter (FIR) and infinite impulse response filter (IIR); whereas adaptive filetrs can be classified as least means square (LMS) and recursive least means square (RLS) filetrs. The transform domain methods include wavelet transform (WT), empirical mode decomposition (EMD) and ensemble empirical mode decomposition (EEMD). Table 2 and Table 3 highlights these filetrs along with their applications, adavantages and disadadvantages respectively.
A brief discussion on these filters is presented below:

A. Digital Filters: FIR and IIR

Digital filters are essential components in digital signal processing (DSP). They are used to eliminate unwanted parts of a signal, such as noise, or to extract useful segments, like specific frequency ranges. Unlike analog filters made with resistors, capacitors, and op-amps, digital filters are implemented through software or digital hardware using mathematical algorithms on sampled data. As mentioned above, the two main types of digital filters are FIR (finite impulse response) filters and IIR (infinite impulse response) filters [5]. Their names are based on the length of their impulse response.

Table 2: ECG denoising methods: conventional

Conventional methods of ECG denoising				
Type of denoising method	**Working principle**	**Application**	**Advantages**	**Disadvantages**
Digital Filters (IIR/FIR)	Uses fixed frequency response to attenuate specific bands.	• **Low Pass:** EMG Noise	• Simple • computationally efficient	• Fixed cutoff frequencies, • Can cause ringing artifacts

Conventional methods of ECG denoising				
Type of denoising method	**Working principle**	**Application**	**Advantages**	**Disadvantages**
		• **High-Pass:** Baseline Wander • **Band-Stop:** Power Line	• real-time capability	(Gibbs phenomenon) • May distort sharp features like QRS
Adaptive Filters (LMS, RLS)	Uses a reference noise signal to dynamically adjust filter coefficients to minimize error.	• Motion Artifacts • PLI when a reference is available.	• Excellent for non-stationary noise • No prior knowledge of signal or noise statistics needed.	• Requires a correlated reference noise signal • Convergence speed and stability can be issues.

Table 3: ECG denoising methods: Transform domain

Transform domain methods of ECG denoising				
Type of denoising method	**Working principle**	**Application**	**Advantages**	**Disadvantages**
Wavelet Transform (WT)	• Decomposes signal into different frequency sub-bands (scales) • Noise is removed by thresholding the coefficients	**All types**, especially EMG and Motion Artifact	• Multi-resolution analysis • Excellent for non-stationary signals • Good at preserving sharp transitions (QRS)	Choice of mother wavelet and thresholding rule is critical and can affect performance.
Empirical Mode Decomposition (EMD)	• Adaptively decomposes signal into Intrinsic Mode Functions (IMFs)	Baseline Wander and EMG Noise	• Fully data-driven • Works well for non-linear and	• Mode mixing problem • Computationally expensive • End effects

Transform domain methods of ECG denoising				
Type of denoising method	**Working principle**	**Application**	**Advantages**	**Disadvantages**
	• Noise is removed by discarding or processing noisy IMFs		non-stationary signals	
Ensemble EMD (EEMD)	An improved version of EMD that uses noise-assisted analysis.	All types, more robust than EMD	• Reduces mode mixing • more stable and reliable than EMD	Even higher computational cost than EMD.

An FIR filter is characterized by its impulse response, which has finite duration. The output of an FIR filter depends only on the current and a limited number of past input samples. The operation of an FIR filter is described by the difference equation as shown in Equation (1).

$$y[n] = \sum_{I=0}^{M} b_i x[n-i] \tag{1}$$

where:

- $y[n]$ is the output signal.
- $x[n]$ is the input signal.
- b_i are the filter coefficients
- M is the filter order. The length of the impulse response is $M+1$.

FIR filters are inherently stable. This is because the impulse response is finite and contains a limited amount of energy. These filters can be designed to have a precisely linear phase response. A linear phase means that all frequency components of the input signal are delayed by the same amount, preventing phase distortion. This is critical in applications like ECG analysis where the shape of the waveform must be preserved.

An IIR filter has an impulse response that is infinite in duration [6]. This is because the output is a function of both previous inputs and previous outputs (feedback). The operation of these filters is described by the difference equation shown in Equation 2:

$$y[n] = \sum_{I=0}^{M} b_i x[n-i] - \sum_{i=1}^{N} a_i y[n-i] \tag{2}$$

In Equation 2, the second summation, which involves past output values $y[n-i]$ represents the feedback which gives the filter an infinite impulse response. IIR filters are not inherently stable. Stability must be checked and ensured during design. These filters have a non-linear hase response. This means different frequencies are delayed by different amounts, which can cause phase distortion and alter the shape of a complex signal like an ECG.

B. Adaptive Filters: LMS and RLS

A typical digital filter, such as FIR or IIR, features fixed coefficients designed for a specific, unchanging frequency response. In contrast, an adaptive filter automatically updates its coefficients based on input signals over time. This adaptability makes it especially effective in situations where signal statistics are unknown or vary over time.

The main principle of operation of an adaptive filter is the minimization of an error signal, $e(n)$, which is the difference between a desired signal, $d(n)$, and the filter's output, $d(n)$ as shown below in Figure 4. The adaptive filters are broadly categorised into two categories the LMS and the RLS. A detailed discussion on these algorithms may be found elsewhere [7]–[9].

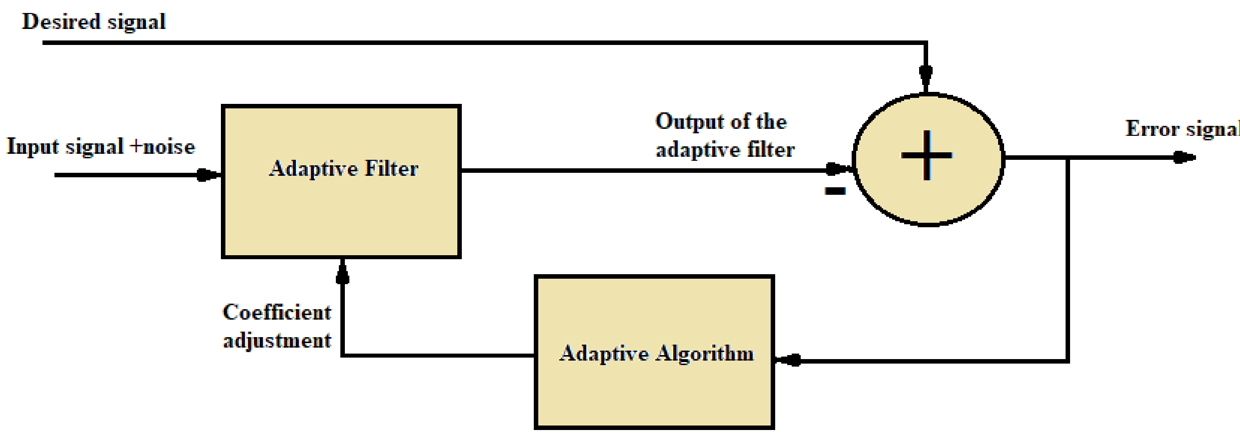


Figure 4: Adaptive noise cancellor

C. Wavelet Transform (WT)

The fundamental idea is to analyze a signal using short, finite-length waveforms called wavelets. Unlike the infinite sine and cosine waves of the FT, wavelets are localized in both time and frequency [10], [11].

A wavelet has two fundamental properties of Zero Mean and Finite Energy [12]. The mother wavelet, denoted by $\varphi(t)$, is a prototype for generating all other wavelets in the analysis. To analyze a signal at different frequencies and time locations, the mother wavelet is operated through scaling (dilation/compression) and shifting (translation) parameters. It decomposes a signal into scaled and shifted versions of a mother wavelet, $\varphi(t)$. Mathematically, the continuous wavelet transform (CWT) of a signal $x(t)$ is defined by Equation 3:

$$W(a,b) = \int_{-\infty}^{+\infty} x(t)\, \varphi^* \left(\frac{t-b}{a}\right) dt \qquad (3)$$

where a represents the scale, b the translation, and $\varphi(t)$ the mother wavelet. The choice of mother wavelet depends on the application.

The another form of wavelet transform is called as discrete wavelet transform (DWT). It is often used in ECG processing due to its computational efficiency. It decomposes the ECG into approximation (low-frequency) and detail (high-frequency) coefficients, allowing noise reduction and extraction of morphological features. Unlike Fourier transformation, DWT offers a multi-resolution analysis approach, allowing more information in both time and frequency domains to be obtained instantaneously. A detailed discussion on wavelet transformation may be found in [13], [14].

D. Empirical Mode Decomposition (EMD) and Ensemble Empirical Mode Decomposition (EEMD)

Methods like Fourier and Wavelet Transforms rely on pre-defined basis functions (sinusoids). The advancement of denoising techniques for ECG signals has reached new heights with Empirical Mode Decomposition (EMD) and its superior counterpart, Ensemble Empirical Mode Decomposition (EEMD). EMD offers a revolutionary, data-driven approach that effectively deconstructs complex, non-linear, and non-stationary signals into intrinsic mode functions (IMFs) [15]. Each IMF captures oscillatory components of varying scales, yet presents the challenge of mode mixing, where disparate oscillations may be improperly grouped together, thereby compromising the fidelity of critical features, such as the QRS complex.

EEMD effectively mitigates this issue by introducing white noise to the ECG signal during the decomposition process. This uniform scale distribution assists in consistently aligning similar oscillations within their respective IMFs. Additionally, averaging results across multiple trials helps to cancel out the effects of noise, thereby enhancing the clarity of the extracted components.

An ECG signal with a sudden burst of EMG noise or a motion artifact can cause severe mode mixing in standard EMD. The QRS complex might get split across multiple IMFs, distorting its shape. EEMD's superior scale separation ensures that the QRS complex is cleanly captured in specific mid-frequency IMFs, leading to a denoised signal with better-preserved morphology.

III. COMPARATIVE ANALYSIS AND DISCUSSION

A number of research papers have been published by various researchers on denoising methods of ECG [5], [8], [9], [15]–[19]. From the survey of those papers, it can be found that there is no one-size-fits-all denoising method for all types of ECG noise. The choice depends on the specific noise contaminating the signal, the computational resources available, and the need for real-time processing. However, some important inferences may be drawn as mentioned below. For simple, stationary noise like PLI, traditional filters remain efficient and effective.

- **For complex, non-stationary noise** like motion artifacts and EMG, transform domain methods like **Wavelet Transform** offer a robust and widely adopted solution, providing a good balance between performance and complexity.
- **Adaptive filters** are unparalleled when a reliable reference noise signal is accessible.

Table 4 summarizes the comparative analysis of these methods.

Table 4: Comparative analysis of different methods

Type of noise	Most effective denoising method	Remarks
Power Line Interference	Adaptive Filtering, Notch Filter	Narrow-band, stationary noise. Adaptive filter is superior if a reference is available.
Baseline Wander	EMD/EEMD, High-Pass Filter (with caution), Wavelet Transform	EMD is excellent at isolating and removing low-frequency drift without affecting the ST segment.
EMG Noise	Wavelet Transform	Wavelets effectively separate random, high-frequency noise from the signal's key components.
Motion Artifacts	Adaptive Filtering, Wavelet Transform, EMD	These methods handle the non-stationary, high-amplitude, and erratic nature of this noise better than fixed filters.

IV. CONCLUSION

This study examines various ECG denoising methods based on both conventional and transform domain techniques, evaluating the different types of noise, their characteristics, and the appropriate filtering methods required for effective removal. Notably, there is no single solution that fits all ECG denoising scenarios, the optimal choice depends on the specific type of noise, available computational resources, and the requirements for real-time processing.

Key findings suggest that traditional filters are effective for simple, stationary noise such as power line interference (PLI). Conversely, for more complex, non-stationary noise, including motion artifacts and EMG interference, advanced techniques like wavelet transform offer a well-balanced solution.

Adaptive filters are particularly useful when a reliable reference noise signal is available. Moreover, in practical situations where sudden bursts of EMG noise or motion artifacts occur, Ensemble Empirical Mode Decomposition (EEMD) stands out by effectively isolating the QRS complex, resulting in clearer ECG waveforms. This enhanced clarity is vital for accurate diagnostics, positioning EEMD as an essential tool for improving ECG signal quality and enabling healthcare professionals to make informed evaluations.

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