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An ECG Signal Denoising Method Using Filtering Techniques

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Abstract:-This study presents a novel approach for denoising electrocardiogram (ECG) signals, aimed at improving their performance and availability under noisy conditions.The suggested method harnesses Conditional Generative Adversarial Networks (CGANs) tailored for the purpose of denoising Electrocardiogram (ECG) data. This approach comprises two essential elements: an improved Convolutional Auto-Encoder (CAE)-driven generator and a discriminator with four convolutional layers and a fully connected layer. It takes advantage of the ECG signal's innate ability to retain spatial proximity and neighboring patterns in more advanced feature representations, aided by skip connections that aid gradient propagation during the denoising training process, the resulting model exhibits strong performance and generalization capabilities. This method incorporates advanced filtering techniques, including IIR notch filters, The combination of l_2 and l_1 trend filtering along with a Kalman filter has been employed to enhance the quality of an ECG signal, rendering it more amenable for subsequent analysis and identification. These filtering methods prove particularly advantageous when dealing with ECG signals exhibiting a high Signal-to-Noise Ratio (SNR). Extensive experimentation conducted using the MIT-BIH database has validated the efficacy of these filtering techniques in effectively eliminating various sources of noise, while preserving the unique characteristics of the ECG signals.

Keywords: *CGAN (conditional generative adversarial network), IIR Notch filter, l2 and l1 trend filtering, MIT-BIH database.*

1. Introduction

The electrocardiogram (ECG) is a vital tool for identifying, diagnosing, and categorizing cardiac disorders. The rise of telemedicine has underscored the growing significance of remote ECG monitoring for automated heart condition diagnosis. However, ECG signals are often plagued by a range of interferences and disruptions, such as baseline wander and electrode motion, which must be eliminated to ensure precise diagnostic assessments. Several traditional approaches are available for enhancing the quality of ECG signals, including adaptive filtering, empirical mode decomposition (EMD), S-transform, wavelet transform, and Fourier decomposition.Recently, wavelet transform (WT) has gained popularity for effectively denoising non-stationary data like ECG and EEG.

In various signal processing applications, such as biomedical signal processing and audio processing, baseline wander noise is mitigated through the use of techniques like Infinite Impulse Response (IIR) notch filters, l2 and l1 trend filtering, and low-pass filters. Baseline wander noise is primarily composed of low-frequency components that can obscure signal interpretation. yet, Separating ECG signals from noise becomes complex when their spectral or energy distributions overlap. In addition to addressing electromagnetic (EM) and baseline wander (BW) noises in ECG signals, more advanced techniques like the stacking contractive denoising auto encoder (CDAE) and its upgraded version, denoising auto-encoder (DAE), have been employed. These methods differ from traditional denoising techniques. Utilizing generative adversarial networks (GANs) for ECG denoising presents a departure from the Denoising Auto-encoder (DAE) method. GANs have demonstrated their efficiency in eliminating individual noise sources and, notably, when combined with residual networks, they have yielded denoised ECG signals with the highest Signal-to-Noise Ratio (SNR) in 2021, However, it has been observed that this strategy may not perform well at low SNR levels. Conditional generative adversarial networks (CGANs) have not been explored for ECG denoising in the GAN-based approaches mentioned. CGAN offers a way to condition data generation, making it suitable for situations where additional information is necessary to guide the denoising process. Conditional Generative Adversarial Networks (CGANs) have made significant advancements within the realm of image processing, finding application in tasks Style transfer, super-resolution, and image inpainting are a few examples. In your methodology, you employ CGAN for the purpose of ECG denoising, Creating a model that incorporates a one-dimensional Convolutional Neural Network (CNN) in tandem with Conditional Generative Adversarial Networks (CGAN).. Additionally, you incorporate the convolutional auto-encoder (CAE) into your strategy.

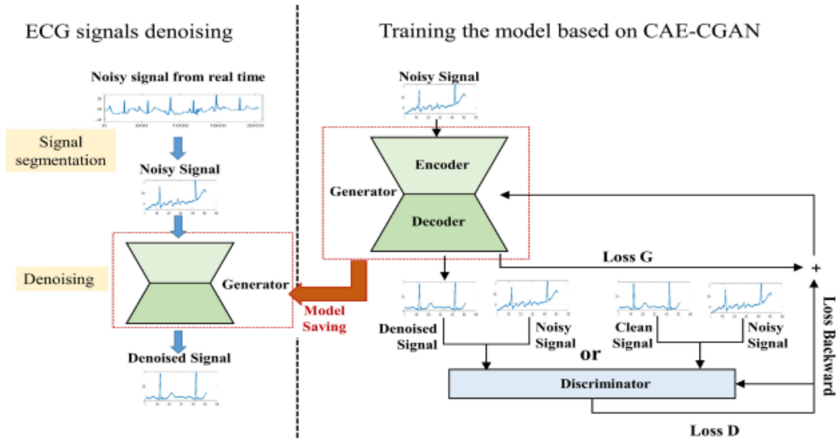

Figure 1 Depicts the typical architecture of the CAE-CGAN designed for ECG denoising.

We suggest a new CGAN built on CAE based on the analyses mentioned above.The CAE-CGAN, a framework built upon Generative Adversarial Networks (GANs),It comprises of a generator as well as a discriminator. Within this framework, the generator, designed with an optimized Convolutional Auto-Encoder (CAE), Produces the cleaned ECG signals. Additionally, the generator uses the discriminator as an auxiliary network to produce denoised ECG signals. Upon the completion of training, a proficiently trained generator can be used to eliminate noise from the ECG data that is polluted with noise.The CGAN framework is generated using the CAE structure. By adjusting the parameters and creating the structure, the optimum CAE structure is created.

1.1 L_2 and L_1 trend filtering:

L_2trend filtering, alternatively referred to as quadratic variation (QV) regularization, employs a linear time-invariant (LTI) filter. It is valuable for smoothing noisy data and detrending time-series signals. This method is effective for achieving smooth trend estimates in data.L_1trend filtering is commonly recognized as total variation (TV) regularization. It is a nonlinear filtering technique that aims to provide sparse derivative trend estimates. This makes it suitable for estimating signals with sparse derivatives, such as piecewise-polynomial signals.

The Kalman Filter is recognized as a fundamental and extensively applied estimation algorithm, serving a crucial role in deriving estimations for concealed variables from measurements that frequently contain errors and uncertainties. Furthermore, the Kalman Filter has the capability to predict future system states based on previous estimations. It is particularly useful in systems with multiple sensors that rely on a sequence of measurements to estimate hidden (unknown) states. To grasp the functioning of the Kalman Filter, it is advisable to establish a fundamental grasp of essential terms,This list encompasses terms like variance, standard

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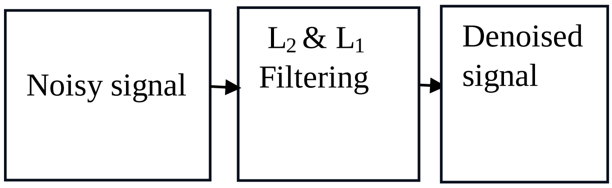
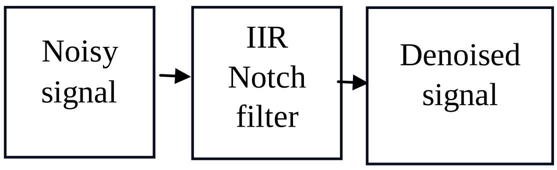
deviation, normal distribution, estimation, accuracy, precision, mean, expected outcome, and stochastic variables. The text introduces a consolidated framework that relies on to perform l_2 and l_1 trend filtering, the Kalman filter (KF) and the Kalman smoother (KS) are employed.This framework is presented as a basis for comprehending the fundamental principles behind these noise reduction methods, as well as for illuminating the distinctions and commonalities between them. The text also asserts that l_2 trend filtering can be considered a subset of l_1 trend filtering. While l_2 and l_1 trend filtering methods are typically used in a non-causal manner in the existing literature, the text suggests that it is feasible to construct these trend filters causally using the provided framework. You can employ the Kalman Smoother (KS) to implement classical Trend filters that are not causative. They can be converted into a causal filter design approach using the Kalman Filter (KF).



The Electrocardiogram (ECG) is an indispensable instrument for evaluating cardiac performance and identifying various heart-related illnesses.However, the accuracy of ECG signals can be compromised by various disturbances. In response to this challenge, our research focused on the development of noise-reduction filters for real ECG signals. We employed the Kalman filter technique to create two denoising filters, namely L2 and L1.To assess the performance of these filters and their effectiveness in noise reduction,The outcomes of our simulations strongly indicate that the Kalman filter is a highly effective tool for denoising ECG signals. It consistently demonstrated excellent performance based on the analysis of these performance parameters.

1.2 IIR Notch Filter:

To remove baseline wander, we aim to design a notch filter that targets the specific frequency range associated with this noise. Baseline wander noise typically consists of low-frequency components that can interfere with the analysis of signals. It relies on the principle of selectively attenuating a narrow band of frequencies, which corresponds to the unwanted baseline wander component in a signal. It refers to low-frequency variations in a signal, often caused by factors like electrode movement, respiration, or external interference. The notch filter is designed to have a sharp attenuation at the center frequency corresponding to the baseline wander component. It's characterized by its center frequency (the frequency you want to attenuate) and bandwidth (the range of frequencies around the center frequency to be attenuated).



The filter's transfer function is typically described using second-order sections or biquad filter structures. The result of applying the notch filter is a cleaner ECG signal with a notable reduction in baseline wander noise. The effectiveness of the notch filter is assessed by contrasting the filtered signal with the original ECG signal.

2. Literature Review

[1] Xiong, Peng, Hongrui Wang, Ming Liu, Feng Lin, Zengguang Hou and Xiuling Liu: In this paper, a new approach called contractive denoising auto encoder (CDAE) is described in order to reduce noise from a specific signal, This approach creates a deep neural network for noise reduction, enhancing ECG signal representations through a multilevel feature extraction process utilizing the Frobenius norm of the Jacobian matrix. The method leverages the MIT-BIH database and offers a distinctive strategy that leads to improved signal-to-noise ratios and reduced root mean square error.

Summary: The denoising technology is being refined further.

[2] Kabir, Md. Ashfanoor and Celia Shahnaz: In this context, we introduce EMD-based ECG denoising, which deviates from conventional methods. In this case, they employed the EMD domain to remove noise from IMFs, allowing them to save the QRS complex signal. This method doesn't consider the number of Intrinsic Mode Functions (IMFs) that encompass QRS complexes or the noise linked to them. Instead, it transforms the signal into theDiscrete Wavelet Transform (DWT) domain, which facilitates the creation of a cleanECG reading. They compared fourdatarecord simulations; as a result, the noise is decreased even more, and there is a strong possibility of producing a more accurate denoised signal.

Summary: A new approach to ECG denoising has been developed.

[3] K X. Lu, M. Pan, Y. Yu: Cardiovascular disease stands as the leading global cause of mortality. For a quick and precise diagnosis, the automatic electrocardiogram (ECG) analysis technique, whose first step is QRS recognition, is essential. Fast computation and low memory requirements are hallmarks of the QRS complex detection threshold technique. In this mobile age, wireless, wearable, and portable ECG systems may quickly alter threshold algorithms. However, there is still room for improvement in the threshold algorithm's detection rate. An improved adaptive threshold approach for QRS detection is described in this study. The key elements of this technique include preprocessing, peak discovery, and adaptive threshold QRS detection. The MIT-BIH has a 99.41% detection rate, a 99.72% sensitivity, and a 99.69% specificity.

Summary: used statistical thresholds to analyze the QRS peaks detection and detected the QRS peaks from an ECG signal

[4] R.M. Rangayyan, John Wiley & sons: Complex phenomena known as physiological processes might include stimulation and control of the nervous system or of hormones, inputs and outputs that can be in the form of chemicals, neurotransmitters, or information, and mechanical, electrical, or biochemical actions. The majority of physiological processes either exhibit themselves as signals or are accompanied by signals that describe their type and activities. The signals could be electrical, such as potential or current, physical, such as pressure or temperature, or biological, such hormones and neurotransmitters.

Summary: studied the physiological procedures involved in identifying the QRS peak from an ECG signal and identified them.

[5] J. Pan, W.J. Tompkins: We have devised a real-time approach for accurately recognizing QRS complexes in ECG signals. This method relies on precise digital analyses of parameters like slope, amplitude, and breadth to differentiate QRS complexes. To enhance its effectiveness, we've implemented a regulated digital bandpass filter that effectively mitigates various types of interference commonly found in ECG data. By employing low thresholds, made possible by this filtering process, we have significantly amplified the system's detection sensitivity. What sets our system apart is its ability to adapt by periodically fine-tuning thresholds and parameters to accommodate variations in heart rate and changes in the shape of the QRS complex. Through the utilization of this method, we have accomplished an impressive 99.3% accuracy in the precise identification of QRS complexes within the MIT/BIH Arrhythmia database.

Summary: we have analyzed and extracted QRS peaks from ECG signals within the MIT/BIH and Arrhythmia databases.

3. Work Description

To extract the ECG signals with no noise, we employed CAE-CGAN and other filters. The adversarial learning process employs a minmax game between two entities, Referred to as G and D, the optimization of the objective function, as outlined below, is pursued in this context.

$$\min_G \max_D = E_{x\sim pdata(x)}[\log D(x)] + [\log(1 - D(G(z))] E_{z\sim pz(z)} \quad (1)$$

Following the introduction of GAN, numerous enhanced versions The GAN may improved by adding extra conditions to make it a conditional version. Information y, which may be anything extra like a class data or labels from different distributions. The purposeful action of "CGAN" is:

$$\min_G \max_D = E_{x\sim pdata(x)}[\log D(x, y)] + [\log(1 - D(G(z, y), y))]\ E_{z\sim pz(z)} \quad (2)$$

In the context of a denoising task , where the input is a noisy signal denoted as x̃ , the values of the discriminator D and the generator G are determined using the Least Squares Generative Adversarial Network (LSGAN) method. LSGAN addresses issues like gradient vanishing by replacing the standard cross-entropy loss with the least square loss.The objective functions for both the discriminator (D) and the generator (G) in LSGAN are as follows:

$$\min_D V_{LSGAN}(D) = \frac{1}{2} E_{x\sim pdata(x)}[(D(x, y) - 1)^2] + \frac{1}{2} E_{z\sim pz(z)}[(D(G(z, y), y))^2] \quad (3)$$

$$\min_G V_{LSGAN}(G) = \frac{1}{2} E_{z\sim pz(z)}[(D(G(z, y), y) - 1)^2] \quad (4)$$

The LSGAN objective function removes the variable z from the equation while introducing the distance metric l_{dist} and the maximum local difference l_{max}. The ldist function computes the variations between the raw signal x and the denoised signal. The smaller the l_{dist}, the higher the denoised quality. l_{max} keeps track of the greatest difference between the Signals that have been denoised and those that have not. The greater the l_{max}, the greater the number of details. The more the ECG signal is retained, the better the medical benefit.

In this context,N denotes the quantitysampled data, where x_n signifiesthe n-th sample of a denoised signal, while x_n stands for the n-th sample of a raw signal. The following is a definition of the loss function for G:

$$\min_G V(G) = E_{x\sim pnoisy}(\tilde{x})[(D(G(\tilde{x}), \tilde{x})) - 1)^2] + \lambda_1 l_{dist} + \lambda_2 l_{max} \lambda_x \quad (5)$$

The term "pnoisy(x̃)" represents the distribution of noisy data in the loss function. To influence the trade-off between different components of the loss function, two weight coefficients, namely λ_1 and λ_2, are employed. Through experimentation, these coefficients have been set to 0.7 and 0.2, respectively. λ_1 and λ_2 allow for the adjustment of the relative importance of the terms ldist and lmax within the objective function.

Furthermore, the loss function for the discriminator has been adjusted to facilitate its learning process . It now assesses (x, x̃) as "true" and (x, G(x̃)) as "false." This modification is integral to the adversarial learning framework and supports the generator's goal of producing more accurate denoised signals.

$$\min_D V(D) = [(D(x, (\tilde{x}) - 1)^2] E_{x\sim pdata(x)} + [(D(G((\tilde{x}), (\tilde{x})^2] E_{x\sim pdata(x)} \quad (6)$$

As performance measures, The root mean square error (RMSE) and signal-to-noise ratio (SNR) are employed as evaluation metrics, and their formulas are provided as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(\widehat{x_n} - x_n)^2} \quad (7)$$

$$SNR = 10\log_{10}\frac{\sum_{n=1}^{N} x_n^2}{\sum_{n=1}^{N}(\widehat{x_n} - x_n)^2} \quad (8)$$

In the context of denoising algorithms, the evaluation parameters primarily focus on "x,"This expression signifies the unprocessed (raw) signal, and "x̂," which represents the denoised signal. These parameters play a central role in assessing the effectiveness of denoising methods. Typically, The impact of the denoising process is evaluated using essential metrics like Signal-to-Noise Ratio (SNR) and RMSE (Root Mean Square Error).

For conducting experiments and obtaining samples, the raw data used was sourced from the datarecord. Thisdatarecord contains 30-minute recordings sampled at a frequency of 360 hertz.

In this context, "x" symbolizes the unaltered (raw) signal, and $\hat{x}$ represents the denoised signal. These are the primary evaluation parameters for denoising algorithms. The denoising effectiveness is directly proportional to

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the SNR, and inversely proportional to the RMSE; in other words, higher SNR and lower RMSE indicate better denoising results.

Denoising Results

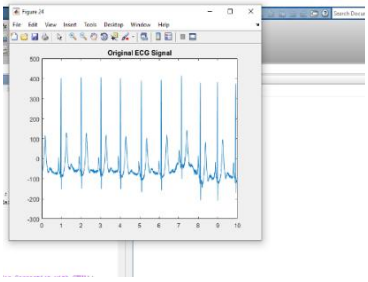

Fig2(a) ECG Signal

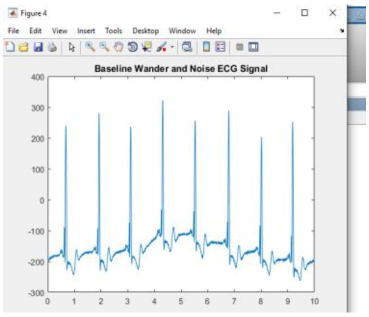

Figure 2(b) Noisy Signal

Fig 2: Denoising eliminates the BW Noise

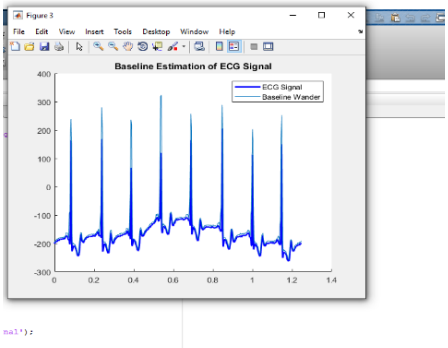

Figure 2(c) Denoised Signal

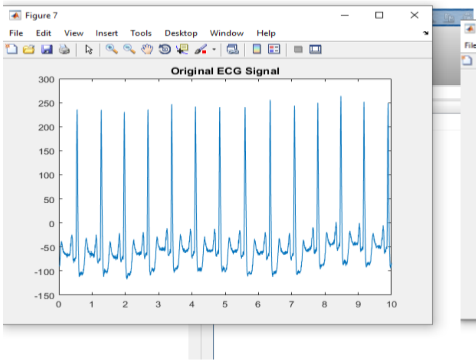

Fig3(a) ECG Signal

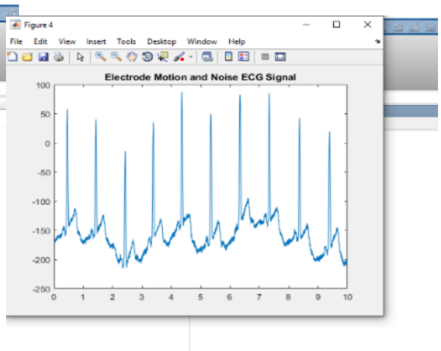

Fig 3(b) Noisy Signal

Fig 3: Denoising eliminates the EM noise

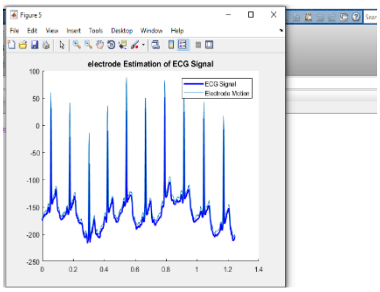

Fig 3(c) Denoised Signal

Figures 2 and 3 illustrateThe figures display the outcomes of noise reduction for baseline wander (BW) and electrode motion (EM) artifacts achieved with our proposed method. In these visual representations,The sub figures are arranged in a top-to-bottom sequence.illustrating the original signals, the noisy signals, and the denoised signals.

It is evident from the figures that the denoised signals, obtained through our proposed method, closely resemble the raw signals. This observation underscores the remarkable effectiveness of our method in efficiently removing two distinct noise types: baseline wander (BW) and electrode motion (EM). The denoised signals closely approximate the original, uncorrupted signals, underscoring the success of our denoising approach.

Denoisingoutcomesforafreshrecorddataseton average

Noise Type	BW		EM	
Denoised metrics	SNR	RMSE	SNR	RMSE
100	39.39	0.0040	25.07	0.0027
106	33.45	0.0074	24.03	0.0050
107	29.28	0.0068	32.76	0.0026
112	23.57	0.0056	32.68	0.0054
117	30.31	0.0072	22.32	0.0035
121	34.53	0.0049	21.81	0.0031
123	28.27	0.0054	23.22	0.0067
124	30.06	0.0089	24.54	0.0033
210	31.72	0.0077	27.93	0.0092
220	29.34	0.0065	27.15	0.0078
Avg	30.99	0.0064	26.22	0.0070

Table 1 Denoising outcomes for a fresh record data set on average

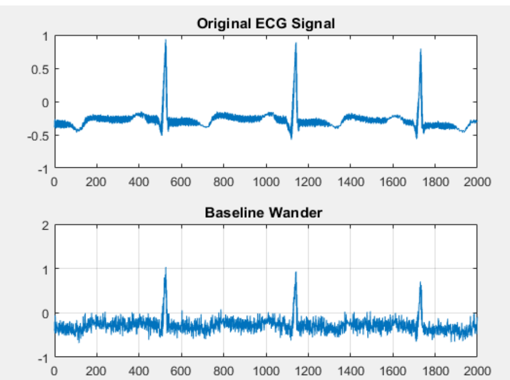

Fig4(a) Unaltered ECG Signal,Baseline Wander removal

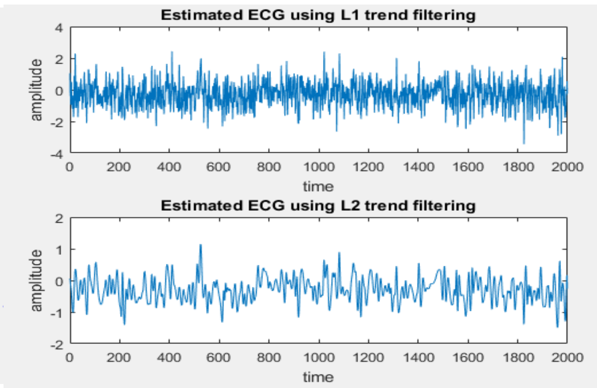

Fig4(b) ECG Reconstruction Utilizing l1 and l2 Trend

Figure 4: Smoothing of ECG signals for record 100m from the MIT-BIH Arrhythmia

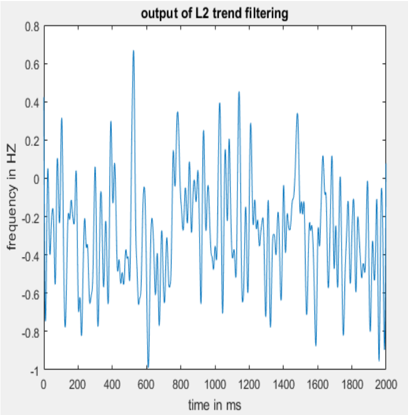

Fig 4(c) ECG Signal Reconstruction with l2 Trend Filtering.

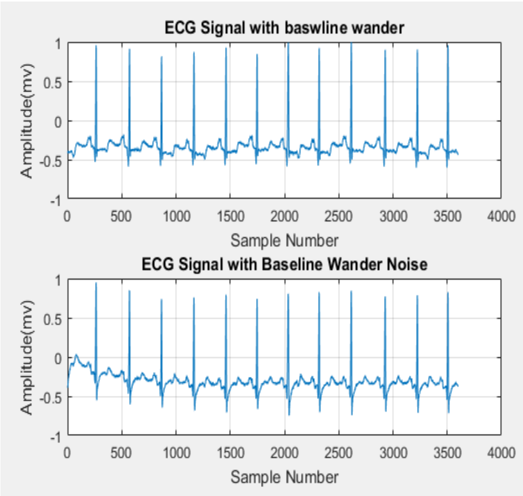

Figure 5: IIR Notch Filter

Utilizing an IIR Notch Filter to Remove Baseline Wander Noise from Record 100 of the MIT-BIH Arrhythmia Database, with the Y-Axis Expressed in millivolts (mV). (a) Represents the ECG Signal, (b) Represents Baseline Wander Noise.

S.no	Data Sets	SNR
1	100	21.85
2	105	18.52
3	112	26.67
4	121	19.98
5	210	23.60
Avg	22.124	

Table 2 :MIT-BIH Arrhythmia Data Base

4. Results and Discussion

The denoising procedure successfully eliminates two noise sources: baseline wander (BW) and electrode motion (EM). Figures 2 and 3 illustrate the results of reducing BW and EM noises through our technology. In these figures, subfigures sequentially display original signals, noisy signals, and denoised signals arranged in a top-to-bottom order.Notably, the denoised signals closely resemble the raw signals, highlighting the efficiency of our method in reducing these two specific source of noise: BW and EM. In Table 1, you will find the Signal-to-Noise Ratio (SNR) and Root Mean Square Error (RMSE) values after reducing noise in 10 records with both baseline wander (BW) and electrode motion (EM) noise. The results offer compelling evidence that our method outperforms others in Signal-to-Noise Ratio (SNR) and Root Mean Square Error (RMSE) across various types of noise.The average SNRs for BW are consistently above 30 dB, while the average SNRs for EM are greater than 26 dB. Our proposed method, which combines l2 and l1 trend filtering with an Infinite Impulse Response (IIR) Notch filter, has successfully eliminated or reduced BW noise, resulting in a clean ECG signal.

For ECG signal smoothing,We applied both L2 and L1 trend filtering techniques to the MIT-BIH Arrhythmia Database. As an example, we have taken a specific case record, such as 100m. The application of L2 and L1 trend filtering for ECG smoothing is demonstrated in the panels. Both L2 and L1 trend filtering algorithms are employed. It is worth noting that L2 trend filtering may cause distortion in the QRS complex; however, This problem can be resolved by fine-tuning the regularization value, Particularly by raising the cutoff frequency.In this case, the structure of QRS complexes is preserved while low-frequency noise is effectively eliminated.

In the IIR notch filter, we employ the direct form-II, as depicted in Figure 5. This involves initially receiving the low-frequency ECG signal, applying the notch filter, and increasing the frequency within the BW noise. Combining this filter with other filters results in more effective denoising and the acquisition of a more accurate ECG signal.

5. Conclusion

The CGAN approach removes unnecessary noise in the signal by utilizing a low pass filter as well as concatenating simplified filters such as the L_2 and L_1 trend filtering and the IIR Notch filter. The proposed approach works well at high signal-to-noise ratios (SNR). Baseline wander (BW) and other disruptions were effectively removed or reduced, resulting in a clear ECG signal. Combining this with additional filters will enhance denoising and yield a more precise signal.

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