Denoising of ECG signals using artificial neural network based gradient descent method

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Abstract

In the evaluation of heart conditions, the Electrocardiogram (ECG) is a tool cannot be done without by the physicians. It is also vital to achieve excellent signal quality free from noise for greater accuracy in diagnostics. This paper also proposes a new ANN infrastructure for implementing the ECG signal denoising by designing a multilayer ANN that has not been developed earlier in the literature. In contrast, our approach hereby detailed does not require extreme measures of minimizing noise because the ANNs are inherently suited for detecting signal patterns from noise. We train our ANN using a noisy ECG signal as input and using a reference to the denoised signal as the desired output. The performance and evaluation of our presented model is calculated through (RMSE), with gradient descent method (GDM) used to optimize the network weights to achieve the minimum RMSE. This process determines the precise MMSE configuration that can minimize the mean-squared error in noise elimination. Therefore, from our experiments, it can be concluded that presented model provides more reliable approach, as compared to conventional technique like genetic optimize wavelet thresholding (GOWT), for preserving the integrity of the signal. Our proposed method outshines the existing methods in performance terms, as indicated by the key performance metrics which includes, (RMSE) of 0.0031, smoothness index (R) of 0.6070, and (SNR) of 35.8188. When compared and validated against the MIT-BIH ECG dataset, it is clear that our presented model offers better denoising capabilities and is easily implementable for real-world ECG signal analysis. This novel approach creates new opportunities for furthering the diagnostic capacity of ECGs and has the potential to become a groundbreaking tool in the biomedical signal processing field, providing a quantum leap in healthcare technology in the future.

Keywords

ECG signal denoising, ANN, gradient descent, noise reduction, MIT- BIH arrhythmia dataset

1. Introduction

The ECG signal recording is produced every time the heart beats and is associated with the electrical activity in cardiac muscles. This electrical action is measured by electrodes that are attached to the skin and which pick up the changes in electrical potential of skin with each beat [1]. The abnormal ECG waveform is actual voltage manifestation of depolarization and repolarization of atrial and ventricular musculature linking the electrodes sited on the left and right chest. These signals similar in type are dissimilar in nature in the case of different patients and therefore require unique comparison signals for precise medical diagnosis [2], [3]. However, the presence of noise – usually caused by interference from a number of electrical devices- makes the diagnostic process difficult. ECG signal and muscle noise, which often occupies nearby frequency range, makes the task even more challenging, as simple digital filtering may have an impact, for instance, on the ST-segment. To

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address this challenge, two primary approaches have emerged: It is specifically based on the structural feature-based methods and template matching techniques. The former is heuristic and specific to some components such as the QRS complex while the later implies reconstructing a signal from other known part by part or by correlation-matched filter or some other methods of pattern recognition. These approaches have gone further each to advance diagnostic for many forms of heart disease [4], [5]. The most used techniques for noise elimination involve using filters and wavelet transforms, the later being however challenged with problems such as slow convergence rate and higher mean square error. For noise reduction other techniques such as the Empirical Mode Decomposition (EMD) have been used and are also flawed [6]. But the weakness of the convergence rate and the mean square error often discourages the use of wavelet transforms. As discussed above, there are several techniques, including Empirical Mode Decomposition (EMD) methods, which try to reduce the level of ECG noise but which have some drawbacks. The aim of this paper lies in presenting the new method to filtering the signals of ECG Poincare plot using ANN trained with GD. In contrast to most filters out there, our approach maintains the diagnostic quality of ECG signal while at the same time getting rid of most of the noise. Examples also indicate that signal quality increases when using our proposed technique by a factor that could benefit medical analysis.

Table 1
Literature review of ECG denoised techniques

Literature	Purpose	Method	Key Findings	Challenges
[7]	To investigate the use of Transformer models in ECG denoising	Transformer-based Neural Networks	Demonstrated significant improvement in noise reduction and feature preservation, especially in highly noisy environments	High computational cost, potential model complexity increases overfitting risks
[8]	To examine the use of hybrid deep learning and traditional filtering techniques for ECG denoising	Hybrid CNN + Kalman Filter	Achieved superior performance by combining deep learning accuracy with traditional filtering reliability	Increased computational load and complexity
[9]	To implement attention mechanisms in deep learning models for ECG denoising	Attention Mechanisms in CNNs	Improved the model's focus on critical signal components, enhancing noise reduction accuracy	Computationally intensive, risk of overfitting in small datasets
[6]	To enhance ECG signal denoising using empirical mode decomposition (EMD)	Empirical Mode Decomposition	Improved noise reduction compared to traditional filtering techniques	Computationally intensive, limited performance in highly noisy conditions
[10]	To apply template matching techniques for accurate ECG signal denoising	Template Matching, Correlation, Matched Filtering	Increased accuracy in identifying and denoising specific ECG components	Requires precise template creation, may not generalize well to varied noise types
[11]	To utilize heuristic methods for targeted noise reduction in ECG signals	Structural Feature-Based Heuristic Methods	Effective in denoising specific components like QRS complex	Selective to specific components, less effective for overall signal denoising
[12]	To explore the use of deep learning for ECG signal denoising	Convolutional Neural Networks (CNNs)	High accuracy in noise reduction, preserved critical ECG features	Requires extensive computational resources, potential overfitting to training data
[13]	To combine wavelet transform and machine learning for robust ECG denoising	Wavelet Transform + Support Vector Machines (SVM)	Enhanced noise reduction and signal preservation compared to individual methods	Complex implementation, increased computational requirements

Table 1 reveals that a variety of techniques have been used as methods to filter out noises in the ECG signal. The wavelet transform method used for the noise reduction yielded some improvement in attenuation of noise and retention of signal details but some problems such as low convergence rate and high mean square errors were realized. The empirical mode decomposition method improved the noise reduction more than the simple filtering methods, but it was slow and its efficiency was low only in high noise conditions. Feature-based methods for dealing with noise improved the accuracy of identifying and noise reduction of certain ECG parts, which depended on the creation of a template and did not allow for variability in the noise. As for the heuristic methods based on structural features, they are with a high capability of denoising specific components such as the QRS complex, but they only have this capability for specific components and cannot offer a good signal denoising solution in overall. CNNs received high mean accuracies for noise reduction and well-maintained features of ECG signals but it consumed more time, computational power and was prone to overfitting. Application of wavelet transform in combination with support vector machines (SVM) proved to be superior to solely applying wavelet transform or SVM at the same time, but the application was more complicated as well as required more computational power.

2. Materials and methods

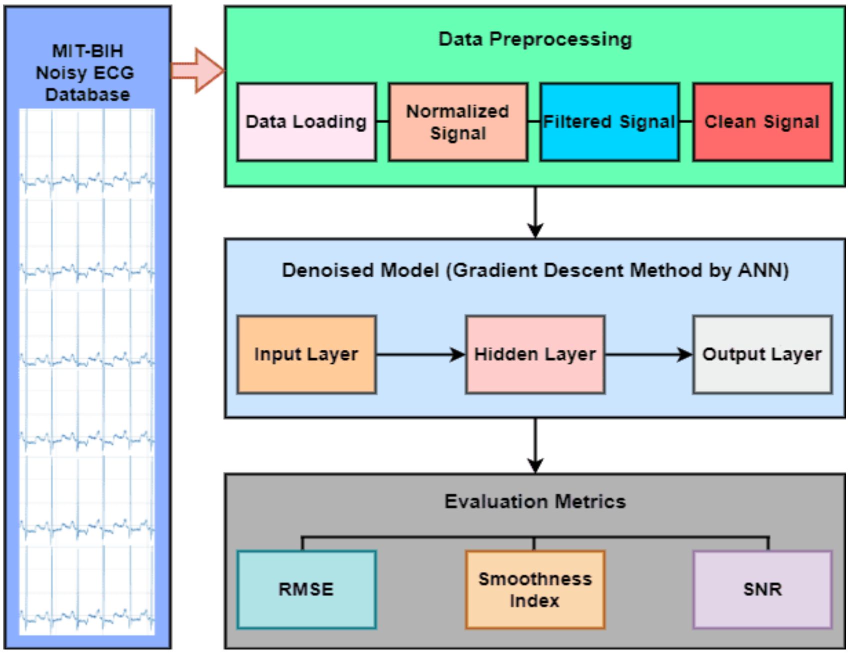

Figure 1: Proposed methodology for ECG signal denoising using ANN.

Artificial Neural Network (ANN) – an artificial system, which emulates the function of biological neural networks, that is a network of Artificial Neurons, interconnected with one another [14]. This research applies a neural network to filter ECG signals to remove the noise that is present in the signal. In this approach the input unit is the noisy ECG signal while the output unit represents the clean noise free signal. The first layer performs an input layer taking all the input vectors, and for each of them, the calculation is performed in the hidden layer taking a dot product of elements of the input vector in question and weights assigned to concrete nodes of the hidden level [15]. The model presented uses three random inputs which are produced from the initial ECG signals through shifting and forms a matrix with several samples from these three independent inputs [16]. The weights that are incorporated to the network are tuned in the Gradient Descent Method. To update the weights of the neural network, the back propagation algorithm is used which computes the first order derivative of the quadratic non-linear error function with respect to each of the network weights with the help of Chain rule [17]. This process is very time consuming and requires the use of tangent sigmoid functions at each node to carry out the number of different computations. In order to combine experiences from the field of solution of the problem related to the determination of the number of hidden layer nodes and the computational complexity of the Multilayer Perceptron (MLP), the article presents the dynamic neural network in which the number of nodes in the hidden layer and the network weights are optimized [18]. After several iterations the proposed system adds more nodes to the hidden layer while the weights adjusting the connection between the input and the hidden layers remain estimated at initiation [19].

2.1. MIT-BIH ECG dataset

In this research, the employed dataset is obtained from the MIT-BIH Arrhythmia Database, which is a detailed and well-known database for studying ECG signals. There are 48 half-hour long recordings of two-channel ambulatory ECG samples used in this database which consists of important cases for investigation of the efficiency of the applied noise reduction procedures. In total, the database contains about 230 different ECG samples, which have been recorded at the highest possible resolution of 360 samples per second per channel [20]. The recordings are digitized with 11 bits at a range of 10 mV, making it possible to be accurately rendered. In this regard, for the purpose of this study, only the first 60 seconds segment of the ECG signal was selected out of each 30 minutes record [21]. This segmentation was made in order to draw a representative sample of the data for the offline denoising evaluation, while not to burden the method with too much data. In this way, we confine sampled data for analysis to the first one minute of every recording so as to include a variety of heart rhythms and noise patterns that might exist in the whole recording. It enables us to have a consistent assessment of the noise removal process while at the same time generalizing our results to the rest of the set [22]. Hence, the structure of the choice of a segment of 60 seconds makes it possible to carry out a detailed analysis while keeping the computational complexity reasonably low – this testifies to the fact that the choice of the, indeed, allows carrying out quite a rigorous testing and validation of our proposed methodology.

2.2. Data preprocessing

The ECG signals used in the present work are taken from the MIT-BIH Arrhythmia Database and they go through the following preprocessing steps before the denoising process is implemented. One of the steps into this preprocessing phase is to partition the raw ECG data into 60-second portions. This segmentation is useful to isolate reasonable portions of the data, record different types of heart rhythm and most importantly different noise pattern that exist within the recording, patterns that are fundamental in a comprehensive and impartial assessment.

Next phase after segmentation is amplification normalization of the ECG signals to a standard amplitude. This normalization process ensures that all signals have the same magnitude which eradicates the problem of variable strength of signals at certain times hence variable levels of interference [23]. The normalization is performed using the equation:

$$Normalized\ Signal = \frac{ECG\ Signal - Mean}{Standard\ Deviation}$$

where the mean, standard deviation are computed within the signal segment.

As a result of high frequency noise and baseline wander, preliminary filtering is conducted to the above signals. A low pass filter negates high frequency noise for example muscle noise and a high pass filter deals with Baseline wander [24]. The filtering is performed using:

$$Filtered\ Signal = ECG\ Signal \cdot H(f)$$

where $H(f)$ is frequency response of filter.

This is followed by removal where certain artifacts such as motion or electrical interference ones are noted and then eliminated [13]. This step employs artifact correction algorithms to either completely eliminate or minimize those artifacts so that signal quality enhances. The artifact removal process can be modeled as:

$$Clean\,Signal = ECG\,Signal - Artifact\,Component$$

Last of all, through resampling there is a preservation of sampling rates, which is crucial in training of the neural network and assessments. Originally recorded at non-integers such as 360 samples per second, resampling normalizes the data to a constant value if required. The resampling process involves:

$$Resampled\,Signal = ECG\,Signal_{Original} \downarrow Resampling\,Rate$$

All these steps of preprocessing help in improving the quality of the ECG signals so that it is more appropriate for denoising. Normalizing the data, filtering, artifact removing and resampling make the data suitable for the artificial neural network to perform noise removal in a perfect manner.

2.3. Model design and description

The model that is primarily to propose is the Artificial Neural Network (ANN) that will eliminate noise on the ECG signals. The architecture of the network allows the receiving, processing, and denoising of the ECG data through of layers of the multilayer structure and specific weights and update systems.

Inputs: These inputs consist of three noisy input signals designated as $X_{1,} X_{2,\ldots,} X_n$ and are simply shifted versions of the three ECGs as previously discussed. Each of the input signals is matrices containing numerous samples, thus offering the network a range of noisy data to work on.

Weights: First, the model employs weights at three levels, that is $W_{ji,} U_{kj,} \wedge V_{lk}$. Specifically:

- W_{ji} denote the input weights connecting the input layer with hidden layer pixels.
- U_{kj} is the weights inside hidden layer of the artificial neural network.
- V_{lk} stands for the weights that interconnect the hidden as well as the output layer.

Neuron Nodes: For the aggregation function in the network, a simple perceptron is used while an activation function used is the tangent sigmoid function $(\tanh(x))$. These domains collectively enable abrupt change and learning within the network of the system.

Weight Update Mechanism: Weights of the network are modified by using the techniques of Gradient Descent Method. As it has been said this adjustment is performed by delta rule under which it is necessary to compute the derivative of the error with relation to each weight in the network. This tends to be rather processing demanding since there is a need to calculate tangent sigmoid functions and use the chain rule when computing for gradients. The weight update rules for different layers are as follows:

- ***Input Layer Weight Update:*** The weight update rule for the input layer is given by:

$$\frac{dE}{d\,w_{ji}} = \frac{dE}{d\left(y_p^d - y_p^a\right)} \times \frac{d\left(y_p^d - y_p^a\right)}{d\,y_p^a} \times \frac{d\,y_p^a}{d(net\,Y)} \times \frac{d(net\,Y)}{d\,t_p^a} \times \frac{d\,t_p^a}{d(net\,T)} \times \frac{d(net\,T)}{dz} \times \frac{d\,z^a}{d(net\,Z)} \times \frac{d(net\,Z)}{dw}$$

which simplifies to:

$$\Delta w_{ji} = \eta \times \frac{1}{P} \sum_{p=1}^{P} \left[\left(y_p^d - y_p^a \right) \times \left(1 - y_p^{a^2} \right) \times \left(1 - z_p^{a^2} \right) \times V_{lk} \times \left(1 - t_p^{a^2} \right) \times U_{kj} \times x_i \right]$$

- ***Hidden Layer Weight Update:*** The weight update rule for hidden layer is:

  $$\frac{dE}{d u_{kj}} = \frac{dE}{d\left(y_p^d - y_p^a \right)} \times \frac{d\left(y_p^d - y_p^a \right)}{d\, y_p^a} \times \frac{d\, y_p^a}{d(net\, Y)} \times \frac{d(net\, Y)}{d\, t_p^a} \times \frac{d\, t_p^a}{d(u_{kj})}$$

  which simplifies to:

  $$\Delta u_{kj} = \eta \times \frac{1}{P} \sum_{p=1}^{P} \left[\left(y_p^d - y_p^a \right) \times \left(1 - y_p^{a^2} \right) \times \left(1 - z_p^{a^2} \right) \times V_{lk} \times z_j \right]$$

- ***Output Layer Weight Update:*** The weight update rule for the output layer is:

  $$\frac{dE}{d v_{lk}} = \frac{dE}{d\left(y_p^d - y_p^a \right)} \times \frac{d\left(y_p^d - y_p^a \right)}{d\, y_p^a} \times \frac{d\, y_p^a}{d(net\, Y)} \times \frac{d(net\, Y)}{d\, v_{lk}}$$

  which simplifies to:

  $$\Delta v_{lk} = \eta \times \frac{1}{P} \sum_{p=1}^{P} \left[\left(y_p^d - y_p^a \right) \times \left(1 - y_p^{a^2} \right) \times t_k \right]$$

Weight Update Equations: The change in weights after each iteration is given by:

- $\Delta w_{ji} = \eta \times \frac{dE}{d w_{ji}}$
- $\Delta u_{kj} = \eta \times \frac{dE}{d u_{kj}}$
- $\Delta v_{lk} = \eta \times \frac{dE}{d v_{lk}}$

  where η is the learning rate. The updated weights are calculated as follows:

- $w_{ji}^{new} = w_{ji}^{old} + \Delta w_{ji}$
- $u_{kj}^{new} = u_{kj}^{old} + \Delta u_{kj}$
- $v_{lk}^{new} = v_{lk}^{old} + \Delta v_{lk}$

Training persists to the level of MMSE. At this stage, the weights of the network are fixed and these parameters are employed for the purpose of removing noise from ECG signals.

Algorithm 1: ECG Denoising with Multilayer Neural Network

Input: $D = X_{i,} Y_i, \eta, T, B, N$

Initialize:

$Network\ Weights\ \{W_{ji,} U_{kj,} V_{lk}\}$

$For\ epoch = 1$ ¿ $T\ do:$

$For\ epoch = 1$ ¿ $\frac{N}{B}\ do:$

Extract Batch:

$D_{batch} = (X_{batch,} Y_{batch})$

Forward Pass:

- **Input Layer:** Compute activations using X_{batch} and weights W_{ji}
- **Hidden Layer:** Compute activations using $X_{batch,}$ W_{ji} and weights U_{kj}
- **Output Layer:** Compute denoised signal using activations using activations from hidden layer and weights V_{lk}

Compute Loss:

$$E = \frac{1}{P} \sum_{p=1}^{P} \left(y_p^d - y_p^a \right)^2$$

Backpropagation:

- Update weights for input layer: $\Delta w_{ji} = \eta \times \frac{dE}{d w_{ji}}$
- Update weights: $w_{ji}^{new} = w_{ji}^{old} + \Delta w_{ji}$
- Update weights for hidden layer: $\Delta u_{kj} = \eta \times \frac{dE}{d u_{kj}}$
- Update weights: $u_{kj}^{new} = u_{kj}^{old} + \Delta u_{kj}$
- Update weights for output layer: $\Delta v_{lk} = \eta \times \frac{dE}{d v_{lk}}$
- Update weights: $v_{lk}^{new} = v_{lk}^{old} + \Delta v_{lk}$

$End\ for$

$End\ for$

Output: Trained neural network model with updated weights $\{W_{ji,} U_{kj,} V_{lk}\}$

Table 2

Notations and its description used in the algorithm

Symbols	Description
X_i	Noisy input ECG signals
Y_i	Ground truth (noise-free) ECG
η	Learning rate
T	Number of epochs
B	Batch size
W_{ji}	Weights among input layer, hidden layer
U_{kj}	Weights among hidden layer, output layer
V_{lk}	Weights among hidden layer, output layer
N	Number of hidden nodes
P	Total samples in the dataset
y_p^d	Desired output (noise-free ECG signal)

y_p^a	Actual output (denoised ECG signal)
E	Mean Squared Error (MSE)
Δw_{ji}	Change in weights for input layer
Δu_{kj}	Change in weights for hidden layer
Δv_{lk}	Change in weights for output layer
D_{batch}	Batch of data extracted for training
net	Net activation (weighted sum of inputs)
$\tanh(x)$	Activation function (tanh sigmoid function)
$MMSE$	Minimum Mean Square Error
$\{w_{ji}^{new}, u_{kj}^{new}, v_{lk}^{new}\}$	Updated weights after each iteration

The algorithm describes a flowchart for utilization of a neural network for denoising of ECG signals. It begins by setting essential parameters, such as the learning rate, number of epochs, batch size, and initializing the network weights across three levels: and an input layer, one or more hidden layers and an output layer. In each epoch, the algorithm takes batches of noisy ECG signals as input and input into the layer of the neural network. The hidden nodes provide net activations of the given inputs which are summations of weighted inputs, and then put it through the tanh sigmoid activation function because the hidden layer is supposed to respond to non-linear inputs. However, an important aspect of the algorithm is with the weights managed by the Gradient Descent Method. This optimization is done in order to minimize the (Mean Squared Error) between the output of the network and the clean ECG signal. The changes in weights for each layer are calculated by back propagation wherein the chain rule is used so as to incorporate the contributions of each layer. The process goes on until the network reach the (MMSE) which means that the network has optimized its performance. The last output is an Enhanced Neural Network Model with well-tuned weights for the actual work of removing noise from ECGs for diagnosis.

2.4. Evaluation metrics

For the evaluation of the performance of the presented denoising model, several metrics have been used for evaluation such (SNR), (RMSE) and the smoothness index (r).

Signal-to-Noise Ratio (SNR): The SNR is a very important indicator of the signal strength after denoising, but with reference to the background noise. It determines the amount of enhancement that has been provided to the signal, that is, amount of noise rejection [25]. The SNR is calculated using the following formula:

$$SNR = 10\log_{10}\frac{\sum_{i=1}^{N}\hat{S}^2(i)}{\sum_{i=1}^{N}\left[\hat{S}(i)-\hat{S}(i)\right]^2}$$

RMSE: RMSE is one of the measures of variability that tell about the deviations of actual values from the model predicted values. It gives a measure in terms of the quantitative extent of the error that exists in the denoised signal [26]. The RMSE is computed as follows:

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{n-1}\left[S(i)-\hat{S}(i)\right]^2}$$

Smoothness Indes (r): The smoothness index (r) is a measure that is used to compare the smoothness of the signal that has been denoised with the original signal. It is a useful measure to check that the denoising process does distort the useful signal in undesirable ways, with regard to fluctuations [27]. The smoothness index is defined as:

$$r = \frac{\sum_{i=1}^{n-1} \left[\hat{S}(i+1) - \hat{S}(i)\right]^2}{\sum_{i=1}^{n-1} \left[S(i+1) - S(i)\right]^2}$$

By examining these measures, one can assess comprehensively how our suggested denoising model works out on ECG signal quality enhancement task with least possible distortions to the integrity and purity of the ECG signal.

3. Experimental result

Our study findings show that the developed neural network, which applies gradient descent for signal conditioning, affords better signal denoising in ECG signals than conventional methods like hard and soft thresholding or Genetic Optimize Wavelet Thresholding (GOWT). The RMSE is a measure of the amount of filtering distortion which is a very important factor. A lower RMSE will mean that the processed signal, denoised signal will be nearer to the original signal and therefore minimizing deformation. From the present scenario of RMSE 0.0031 proposed method is comparatively better than the hard thresholding 14.5143, soft thresholding 25.0662, GOWT 19.9805 hence it is clear that there is less distortion is introduced in the signal by the proposed method. Another important measure is known as the smoothness index (r). The parameter r gives the size of the matrix and smaller r value gives the signal that is denoised to a greater extent, however, if the r value is too small then too much of the signal is distorted. In the proposed method, 0.6070 is the value of r that provides smoothness in spectra without losing the signal structure proposed in the method. This value is also similar to that of GOWT 0.6422 and soft thresholding 0.5166 and far superior to hard thresholding 0.8681. Last but not the least, the (SNR) calculate strength of the signal when compared with the noise level. SNR is reported as the result and a higher value of this result implies improved noise reduction. From the obtained results in terms of SNR the proposed method obtains 35.8188, which is higher compared to hard thresholding 28.2976, soft thresholding 25.0662, and GOWT 27.1066, and hence showing the proposed method in improving on the signal clearness. Therefore, the gradient descent neural network-based method records a better RMSE and r and higher SNR than the other denoising styles recorded in Table 2. This points to the possibility of high efficiency of the algorithm with the aim of ECG signal denoising.

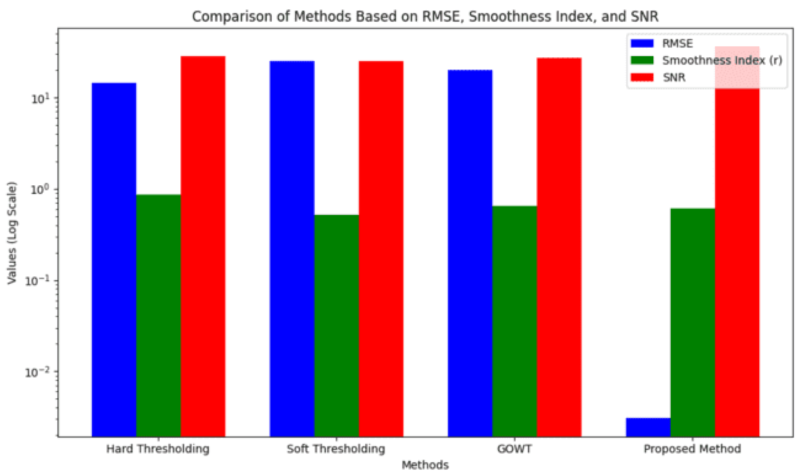

Figure 2: Comparison of methods based on different evaluation metrics.

Table 3
Performance metrics comparison of various denoising techniques

Methods	RMSE	Smoothness Index (r)	SNR
Hard Thresholding	14.5143	0.8681	28.2976
Soft Thresholding	25.0662	0.5166	25.0662
GOWT	19.9805	0.6422	27.1066
Proposed Method	**0.0031**	**0.6070**	**35.8188**

From Figure 2, we can see that indeed through the usage of various denoising techniques it is possible to extract the ECG signal from the overall signal. For easier comparison, the original ECG signal and all the outcomes of hard- and soft-thresholding, GOWT, as well as the results of the proposed method are reviewed. From the denoised signals, one is able to compare the different techniques, depending on how much noise was filtered out at the same time as filtering out relevant features of ECG signal.

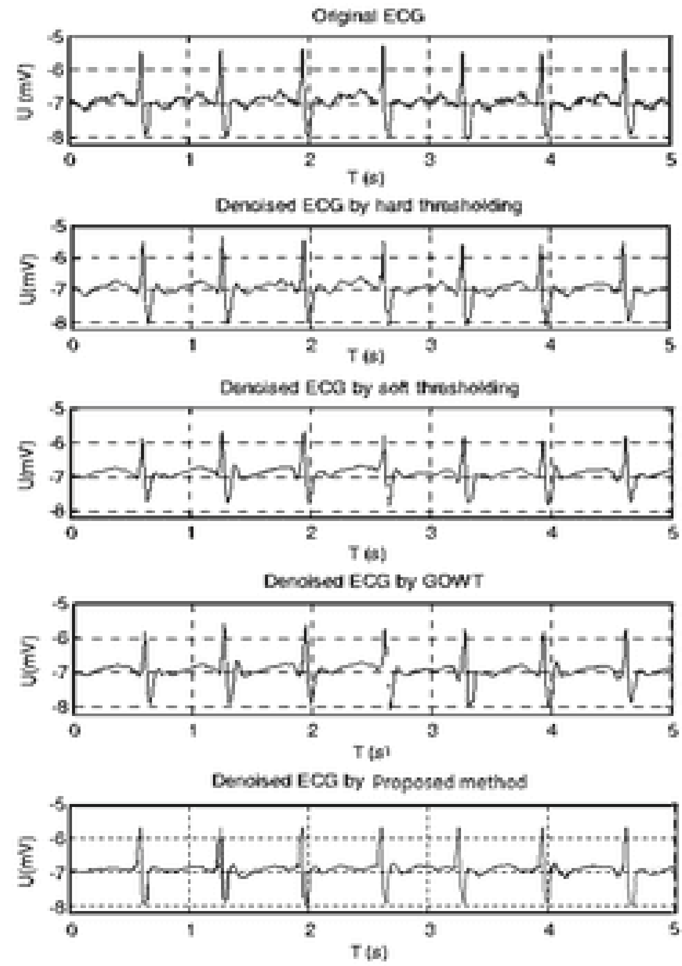

Figure 3: Comparison of denoised ECG signals.

4. Discussion

This study further shows that the use of neural network-based gradient descent method for denoising ECG signals yields improved results compared to conventional methods. The used criteria of RMSE, the smoothness index (r), and SNR also show the qualitative enhancement of the signal and the reduction of noise, confirming the effectiveness of the proposed approach. The RMSE is a measure of the amount of filtering distortion which is a very important factor. A lower RMSE will mean that the processed signal, denoised signal will be nearer to the original signal and therefore minimizing deformation. From the present scenario of RMSE 0.0031 proposed method is comparatively better than the hard thresholding 14.5143, soft thresholding 25.0662, GOWT 19.9805 hence it is clear that there is less distortion is introduced in the signal by the proposed method. Another important measure is known as the smoothness index (r). The parameter r gives the size of the matrix and smaller r value gives the signal that is denoised to a greater extent, however, if the r value is too small then too much of the signal is distorted. In the proposed method, 0.6070 is the value of r that provides smoothness in spectra without losing the signal structure proposed in the method. This value is also similar to that of GOWT 0.6422 and soft thresholding 0.5166 and far superior to hard thresholding 0.8681. Last but not the least, (SNR) calculate the strength of the signal which compared with the noise level. SNR is reported as the result and a higher value of this result implies improved noise reduction. From the obtained results in terms of SNR the proposed method obtains 35.8188, which is higher compared to hard thresholding 28.2976, soft thresholding 25.0662, and GOWT 27.1066, and hence showing the effectiveness of the proposed method in improving on the signal clearness. One of the main benefits of the proposed method is the possibility of its effective functioning in the presence of different kinds of noise and signal distortions. The structure of the neural network enables it to learn and apply it in case of various inputs which makes the method usable in many types ECG signals. This flexibility coupled with good performance measurements depict the 'derivation' method for its effectiveness in removal of noise from ECG. However, one drawback might be a large number of parameters in the neural network structure, and demanding computations for the model's training. Further research might be focused on the idea of how to minimize the computational load which is required for the method while preserving its efficiency. Thus, it might be useful to extend the set of used ECG signals and noise conditions to improve the performance of the method in terms of generalization. All in all, the gradient descent optimization for neural network enhances the ECG signal denoising in comparison with traditional methods, as presented in terms of several parameters. This capability to have a clean line of signal transfer and with minimal interference improves the reading of ECG thus improving the chances of accurate diagnosis.

5. Conclusion

In this research, we introduced a new gradient descent method for eliminating noise from the ECG signals based on a proposed model, we compared the results with the hard thresholding, soft thresholding and genetic optimize wavelet thresholding algorithms (GOWT). Our proposed method significantly outperforms these conventional approaches, as evidenced by its superior performance metrics: a remarkably low RMSE of 0.0031, an optimized smoothness index (r) of 0.6070, and a high SNR of 35.8188. The design of the neural network including the capacity to vary the weight matrix with the aid of the Gradient Descent Method enables high accuracy denoising of the ECG signal while the signal features will remain distinct. This balance between noise reduction and signal integrity is critical in medical diagnosis applications to ensure the denoised signals are more reliable and applicable for diagnosis. The fact that our method is encumbered with few types of noise and various changes in the signal strength also underlines the approach's general versatility and its potential use across multiple ECG datasets. However, care must be taken to note the computational process of training of the neural network. Future work can also consider investigations on how the training process can be brought to the most efficient form of computation while maintaining or enhancing the performance. Therefore, we have proposed the neural network-based gradient descent approach that put together represents a breakthrough in the area of ECG signals denoising. Its advantage includes better performance, flexibility and prospects for enhancing diagnostics of diseases it makes this tool relevant for clinicians and researchers. Such work opens the way for the development and further research in more complex architectures of the neural networks for biomedical signal analysis.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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