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Research paper

ECG signal de-noising based on deep learning auto encoder and discrete wavelet transform

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Abstract

ECG is very important tool for diagnosis of heart disease, this signal is suffered from different types of noises such as baseline wander (BW), muscle artifact (MA) and electrode motion (EM) , which lead to wrong interpretation. In order to prevent or reduce the effect of these noises, different approaches have been applied to enhance the ECG signal. In this paper, we have proposed a new method for ECG signal de-noising based on deep learning Auto encoder (DL-DAE) and wavelet transform named as (WT-DAE). The proposed system (WT-DAE) is constructed from two stages, in the first stage, the wavelet transform is used to isolate the most significant coefficient of the signal (approximation sub-band) from de-tails coefficients (details sub-band). The details coefficients is fed to new proposed threshold method , which is used to evaluate the threshold value according to the feature of ECG signal, this threshold value is used to threshold the detail coefficients, in order to remove the details noise that is contained as high frequencly component , then invers wavelet transform is used to reconstruct the signal . Different wavelet filters and threshold functions are applied in this stage. The second stage of signal de-noising is performed by using DAE method, which is designed for reconstruct the de-noised sig-nal. The proposed DAE model is constructed from 14 layers of convolutional, relu and max_ pooling layer with different parameters. We perform training and testing the model with MIT-BIH ECG database and the performance of the pro-posed system is evaluated by terms of MSE, RMSE, PRD and PSNR. The experimental results are compared with other approaches and show that, the proposed system demonstrated the superiority for de-noising ECG signal.

Keywords: *WT-DAE; ECG; DL; DWT and De-Noising Auto Encoder*

1. Introduction

The most leading cause of death is the cardiovascular disease (CADs). Arthymia, which is irregular heart beat or rate is the most leading to sudden death. Electrocardiogram (ECG) is used as promising diagnostic tool for examining cardiac tissues and structures because it reflects the electrical activity of the heart. The electrical activity is recorded using electrodes that is placed on the skin over a period of time and represented by different waveforms.

This signal contains a significant information about the structure of the heart and its electrical conduction function, for this reason, it is used for diagnosis of diseases, classification of heartbeat, etc. ECG widely applied in the fields of disease classification, heartbeat up normal detection, recognition and biometric identification, so this signal is very important tool and low cost indicator used for effective diagnosis and examining tissue structure [1,2].

In order to use ECG signal to support doctor in diagnosis, it should be clear and smooth signal as possible. Unfortunately, this signal is suffered from different types of noises such as baseline wander (BW), electrode motion (EM) and muscle artifact (MA). Baseline is low frequency can be arises from breathing, skeletal muscle activity generate muscle artifact, while the change in the electrode skin impedance will cause electrode motion noise.[3], [4] So, the aim is to remove these noises , while keeping the original signal as much as possible , since the challenge task is that, the frequencies of the signal is overlapped with the noise .[5] Different method and approaches have been proposed based on different techniques. Many approaches used wavelet transform in signal de-noising, it is used to remove the 50/60 Hz power interference from the signals [6], [7]. In this paper, we have proposed a new method for signal de-noising based on deep learning by using auto encoder (AE) with the wavelet transform to remove the most types of the noises. The main our contributions in this paper are:

- Used the proposed threshold method with wavelet transform to enhance ECG signal.
- Design anew DAE model
- Design anew de-noising system (WT-DAE) based on combining wavelet transform with threshold method and DAE deep learning model.

2. Literature survey

Jing Jianget.al in (2019) proposed a new method to solve the problem of imbalance in the training data, this method is based on three methods, BLSM which are based on aspects of resampling by adding oversampling data , CTFM integrate feature extraction and the feature that are selected, and two phase training (2PT) in which, they are used two training, the first training by using convolutional neural network, while the second is used for tuning the model with original data.[8].
Mohammed almoahamdy and Bryan riley in (2014) proposed a system for ECG signal de-noising based on discrete wavelet transform to remove the power line noise interference. They used adaptive filters, which can change its weight based on the mean square error (MSE). [9].
Ilham Muhammadet.al, (2017) proposed stack de-noise auto encoder with, three , four layer and five layers and ,they used normalization to normalize the data, then used segmentation to detect QRS complex signal to used later in signal classification , they satisfied best result when they are used three layer in (SDAE).[5]
In (2018) Alan S. Said Ahmad et.al, used DWT to de-noise the signal, they used Genetic algorithm to select the best DWT filter type, levels, threshold methods and to denoise ECG arrhythmia signals corrupted by AWGN. The original ECG signal is applied to DWT with different filter types, different levels, then different threshold methods is applied to wavelet coefficients and functions, the invers wavelet transform is used later to reconstruct the enhanced signal. The optimal parameters, wavelet levels and filters are determined by the Genetic algorithm.[10]

3. Methodology

In this paper, we have proposed a new system for ECG signal de-noising based on de-noising auto encoder with discrete wavelet transform (WT-DAE). Figure (1) describe the flowchart of the proposed system. The system is constructed from hybrid of WT and DWT model, a new threshold method has been proposed , which is applied to the detail coefficient of wavelet transform, while the designed DAE model is used as second stage for further enhancement of ECG signal
The discrete wavelet transform is applied to the original ECG signal to transform the signal into approximation coefficients (most important information), which remain unchanged and details coefficient , which will be thresholded by the proposed adaptive threshold method to remove the noise, then invers wavelet transform is used to reconstruct the signal. The second stage of de-noising is performed by DAE model, which is applied to further enhance the signal.

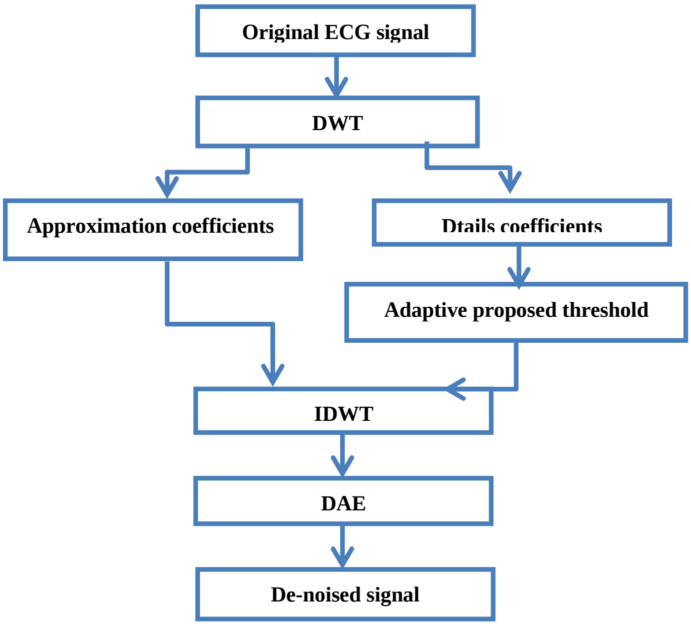

Fig. 1: Flowchart of the Proposed System.

3.1. Proposed threshold method

The threshold value should be chosen based on the signal , and because that, there is different characteristics for each signal , different threshold values should be evaluated based on the features of the signal , we have proposed anew threshold method to be used in the proposed system , which is shown in figure (2).

1. ***Chose initial threshold th=median(details), i=1,n=1,k=1,S=size(detail)***
2. ***While ($i \le S$)***
If detail(i)> th th1(n)=detail(i), n=n+1,
Else th2(k)=detail(i), k=k+1
End
End While
3. ***A1=absolute (th1)***
M1=mean(A1)
Segment1= (M1/ 0.6745)
A2=absolute (th2)
M2=mean(A2)
Segment2= (M2/ 0.6745)
4. ***Segment= (Segment1 + Segment2)/2***
5. ***Threshold=*** $\frac{segment * \sqrt{2 * log10(detail)}}{2^j}$
Where j wavelet level, detail is detail coefficient of wavelet transform

Fig. 2: Proposed Threshold Method.

3.2. DAE design

Figure (3) show the descriptions of the DAE design, at first , the dataset is split into testing and training set, augmentation are used by applying stretching and amplifying to the signal as shown in figure (4) , the augmentation is used to increase the dataset and to increase the accuracy of the model. The training dataset are used for training the designed model, and the parameters of the model are adjusted until the required accuracy is satisfied. Then model weight is saved to be tested by testing set. We have design DAE model, which is constructed from (14) layers , the number of filter are 64,32 and 16 at encoder and 16,32,64 at decoder , Max pooling is used to reduce the cost, while up sampling is used at decoder to reconstruct the original signal length.

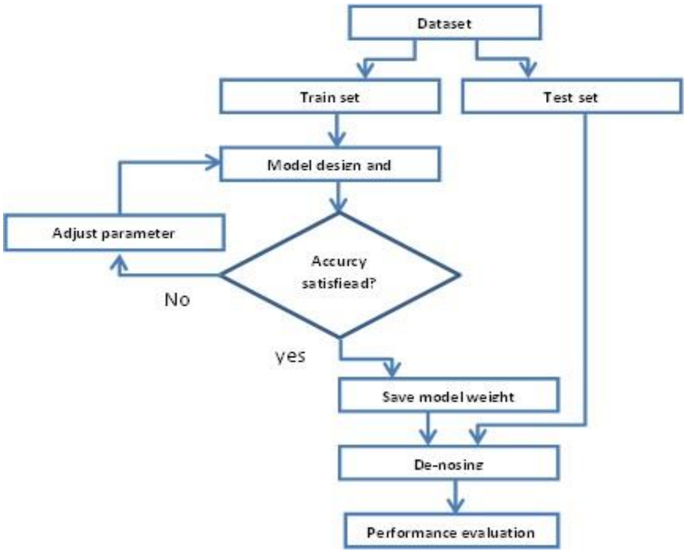

Fig. 3: Flowchart of the Proposed DAE.

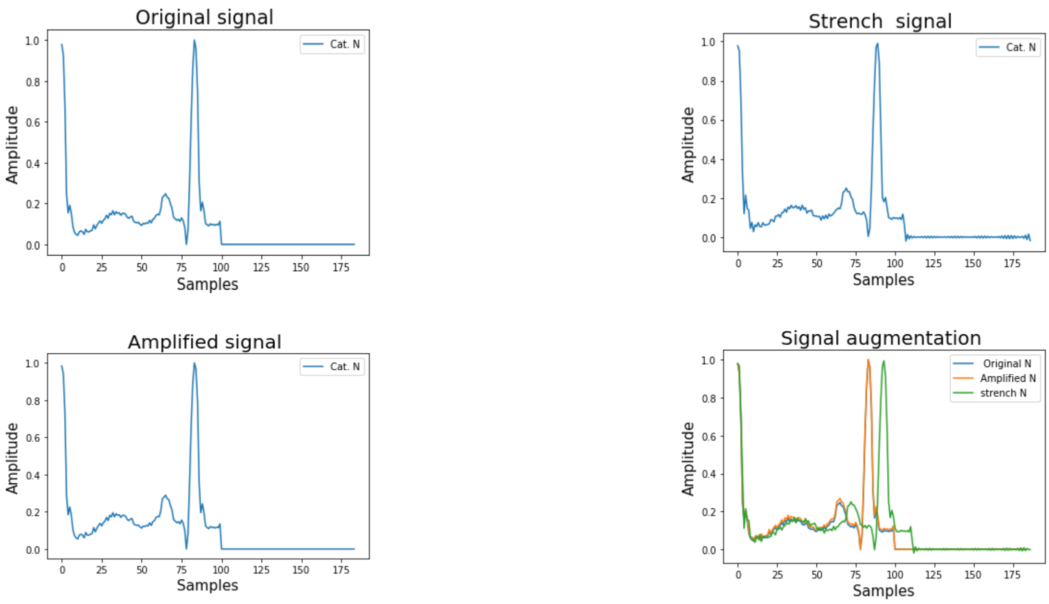

Fig. 4: Original, Starch, Amplified and Augmentation Signals for Normal Signal.

The design of the model represent the most significant part of the system, in it , we have used 14 layers for encoder and decoder with different filters values as described at Table (1).

Table 1: The Details of the Proposed DAE Model

Layer (type)	Output Shape	Parameters
input_1 (InputLayer)	(None, 184, 1)	0
conv1d_1 (Conv1D)	(None, 184, 64)	192
max_pooling1d_1 (MaxPooling1	(None, 92, 64)	0
conv1d_2 (Conv1D)	(None, 92, 32)	4128
max_pooling1d_2 (MaxPooling1	(None, 46, 32)	0
conv1d_3 (Conv1D)	(None, 46, 16)	1040
max_pooling1d_3 (MaxPooling1	(None, 23, 16)	0
conv1d_4 (Conv1D)	(None, 23, 16)	528
up_sampling1d_1 (UpSampling1	(None, 46, 16)	0
conv1d_5 (Conv1D)	(None, 46, 32)	1056
up_sampling1d_2 (UpSampling1	(None, 92, 32)	0
conv1d_6 (Conv1D)	(None, 92, 64)	4160
up_sampling1d_3 (UpSampling1	(None, 184, 64)	0
conv1d_7 (Conv1D)	(None, 184, 1)	129

3.3. Proposed algorithm

In this paper, we have proposed a new system for ECG signal de-noising based on wavelet transform and de-nosing auto encoder (WT-DAE), this system can be summarized by the following steps:
Step1: Read the original ECG signal
Step2: Pre-process it, the original signal have different number of sample ,it is need to be converted to the specified length of samples, the proposed DAE need number of 184 to be down sample to 92,46 and 23 respectively at encoder ,then its up sampled to its original number in decoder stage.
Step3: Apply wavelet transform to split the original signal into approximation coefficients and detail coefficients by suing different wavelet levels.
Step4: The proposed threshold method are used to threshold the details coefficient of wavelet transform.
Step5: Reconstruct the signal by applying invers wavelet transform.
Step6: The reconstructed signal is used as input to the proposed DAE model.
Step7: Calculate the performance metrics of the algorithm.

4. Metric evaluation [11]

In order to measure the performance of the proposed system, we have used different metrics, these metrics are listed below:

4.1. Mean square error (MSE)

This metric represent the mean square difference between the de-noised and original signal and it is determined by:

$$\mathrm{MSE} = \frac{1}{N}\sum_{k=1}^{N}(\mathrm{Xi} - \mathrm{Xr})^2 \tag{1}$$

4.2. Root mean square error (RMSE)

This measure the root square of the square difference between the reconstructed and the original signal and calculated by:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(\mathrm{Xi} - \mathrm{Xr})^2} \tag{2}$$

4.3. Percent RMS difference (PRD)

This measure is used to calculate the quality of the reconstructed signal, it is expected to be as low as possible, and it is calculated by:

$$\mathrm{PRD} = \sqrt{\frac{\sum_{k=1}^{N}(\mathrm{Xi} - \mathrm{Xr})^2}{\sum_{k=1}^{N}(\mathrm{Xi})^2}} * 100\ \% \tag{3}$$

4.4. Signal to noise ratio improvement (SNRimp)

This measure the signal as compared with noise to describe the quality of the signal, it represent the difference or the improvement in the signal between the output and the input noisy signal and it is determined by the following equations:

$$\mathrm{SNR\ inp(dB)} = 10 * log10\frac{\sum_{k=1}^{N}(\mathrm{Xi})^2}{\sum_{k=1}^{N}(\mathrm{Xn} - \mathrm{Xi})^2} \tag{4}$$

$$\mathrm{SNR\ out(dB)} = 10 * log10\frac{\sum_{k=1}^{N}(\mathrm{Xi})^2}{\sum_{k=1}^{N}(\mathrm{Xr} - \mathrm{Xi})^2} \tag{5}$$

$$\text{SNR imp(dB)} = SNR\ out - SNR\ inp \tag{6}$$

Where Xi represent the original signal, Xn noisy signal, Xr reconstructed signal and N represent the number of samples in the signal.[11]

5. Results and discussion

In this paper, we have design de-noising system based on discrete wavelet transform and de-noising auto encoder (WT-DAE) , in which, the DWT is used with different filters types. While in the second stage (DAE), the proposed model is training with MIT-BIH Arrhythmia dataset, which is contain 48 record with sampling frequency 360Hz with 11 bits over 10mv.[12,13] The database was (155938) signal , 105938 for training and 4000 for testing, each signal with 184 samples , these data was augmented by use stretch and amplified methods. The model is training for 50 Epochs. DWT are applied with different parameters, also the results are determined.

5.1. Results of DWT

We have used different types of wavelet filters dB2,dB4,dB6,dB8 and bior4.4, these filters applied with different levels .Table (2)describe the performance of de-noising method by terms of RMSE,MSE and PRD for different levels by using db6 filter, from table it is clear that level three give the best results (3.82 dB). The performance of the wavelet filters types by using hard threshold method are explained In Table (3), from it, dB4 filter give best value in terms of (SNR imp) (3.82), also dB4 reduce the values of MSE and RMSE to 0.019048 and 0.00036625 respectively.

Table 2: Performance Metric for Db4 With Different Levels

Level	MSE	RMSE	PRD	SNRimp
Level1	0.00045393	0.021306	10.9649	2.8478
Level2	0.0003898	0.019743	10.1609	3.5092
Level3	0.00036283	0.019048	9.8031	3.8206
Level4	0.00036625	0.019138	9.8492	3.7799
Level5	0.00036627	0.019138	9.8494	3.7797

While Table (4) show the performance measures for different filters by using soft threshold function. The best results in term of SNRimp are satisfied by use db6 filter.

Table 3: Performance Metric for Different Wavelet Filters (Hard Threshold)

Filter type	MSE	RMSE	PRD	SNRimp (dB)
db2	0.00042883	0.020708	10.6575	3.0948
Db4	0.00036283	0.019048	9.8031	3.8206
Db6	0.00041091	0.020271	10.4324	3.2802
Db8	0.00051409	0.022674	11.669	2.3072
Bior4.4	0.00042579	0.020635	10.6197	3.1257

Table 4: Performance Metric for Different Wavelet Filters (Soft Threshold)

Filter type	MSE	RMSE	PRD	SNRimp (dB)
db2	0.00041788 RMSE =0.020442 PRD =10.5205 SNRindB=16.3521 SNRoutdB=19.5593 SNRimp=3.2072 Db22	0.020442 PRD =10.5205	10.5205	3.2072
Db4	0.00034989 RMSE =0.018705 PRD =9.6267 SNRindB=16.3521 SNRoutdB=20.3305 SNRimp=3.9784 Db44	0.018705	9.6267	3.9784
Db6	0.00027679 RMSE =0.016637 PRD =8.5622 SNRindB=16.3521 SNRoutdB=21.3483 SNRimp=4.9962 Db66	0.016637	8.5622	4.9962
Db8	0.00033822 RMSE =0.018391 PRD =9.4649 SNRindB=16.3521 SNRoutdB=20.4777 SNRimp=4.1256 Db88	0.018391	9.4649	4.1256
Bior4.4	0.00032236 RMSE =0.017954 PRD =9.2402 SNRindB=16.3521 SNRoutdB=20.6863 SNRimp=4.3342 Bior22	0.017954	9.2402	4.3342

The difference between the original and reconstructed signals are shown in figure (5), (6) for db4 and dB6 filters respectively

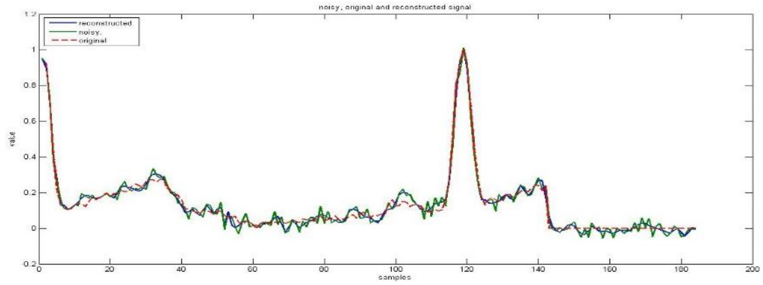

Fig. 5: Original, Noisy, and Reconstructed Signal for ECG for Db4 Filters.

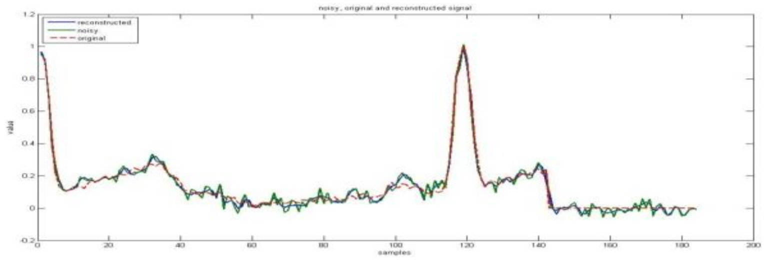

Fig. 6: Original, Noisy, and Reconstructed Signal for ECG for Db6 Filters.

5.2. Results of DAE model

We have proposed two models in this paper, the first model layers is described in table (1),in it the filters was 64,32,16 in encoder and 16,32,64 at decoder, while the second model is similar to the first model except the number of filters are become 128,64,32 at decoder. The models are trained to 50 Epochs after augmentation of the original data with stretch and amplified method. The loss function of the model is shown in figure (7).

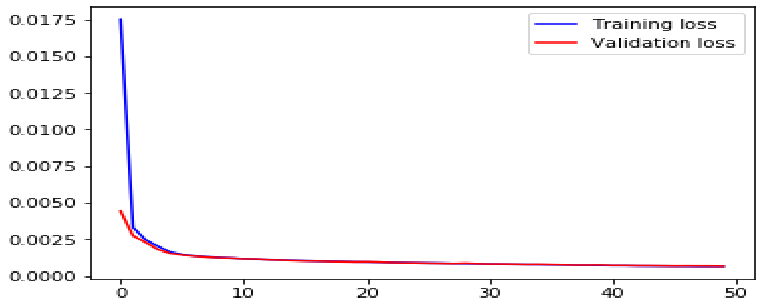

Fig. 7: The Training of the Proposed DAE Model.

The model satisfied training loss $3.36*10^{-4}$ and validation loss $3.456*10^{-4}$,RMSE 5.996% and MSE was 0.000345 .The training model is applied to de-noise different ECG signal with different SNR inp and the results of model one and model two are listed in Table (4).

Table 5: Result of Model1 and Model2

Signal	model	MSE	RMSE	PRD (%)	SNRimp(dB)
Signal1	Model1	0.000427	0.02o67	4.4057	1.816
	Model2	0.00043	0.02073	4.4215	1.78
Signal2(	Model1	0.0004	0.02024	6.53	2.301
	Model2	0.00048	0.0219	6.71	2.26
Signal3	Model1	.0000919	.0095	7.995	2.76
	Model2	0.000488	0.0221	7.05	1.44
Signal4	Model1	0.00065	0.0256	4.96	1.3
	Model2	0.000848	0.0291	5.6448	1.19
Signal5)	Model1	0.00032	0.0181	8.558	2.9
	Model2	0.000348	0.01866	8.882	2.63

The original, noisy and reconstructed ECG signals by use the designed model1 are shown in figure (8), while figure(9) show the results for model2.it is clear from figures and tables that model1 give better results than model2.

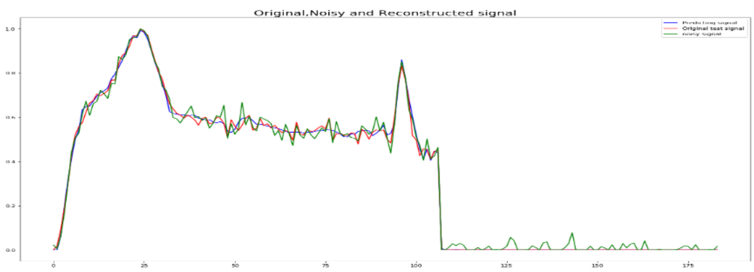

Fig. 8: Original, Noisy, and Reconstructed Signal by Proposed Model1.

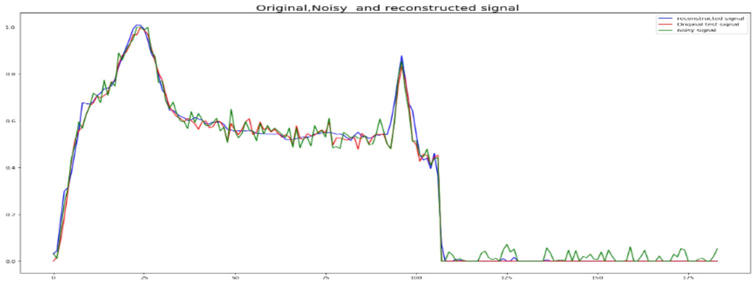

Fig. 9: Original, Noisy and Reconstructed Signal by Proposed Model2.

5.3. Result of (WT-DAE) system

The result of using different wavelet levels by applying the proposed method is shown in table (6), the best result in term of SNRimp is satisfied at level three(6.26 dB) while the lowest result at level two , at level four and five, the value is decreased to (6dB). Also, there is high improvement in the values of SNR imp for the proposed method as compared with using wavelet transform only as shown in figure (10). Also there are high decreasing in the value of RMSE and PRD values compared with the result obtained by using wavelet method only as shown in figure (11) and figure (12) respectively. Table (7) describe the results of the proposed system with db2 filter, the result show that the best SNRimp value is satisfied at level one and level three, the same matter for RMSE and PRD value.

Table 6: Result of Proposed Method with Different Levels for Db4 Filter.

Level	MSE	RMSE	PRD	SNRimp
Level one	0.0002135	0.014612	7.52	6.14
Level two	0.00031	0.01770	9.1114	4.56
Level three	0.000220	0.014846	7.64	6.26
Level four	0.0002197	0.0148	7.629	6.02
Level five	0.0002197	0.0148	7.629	6

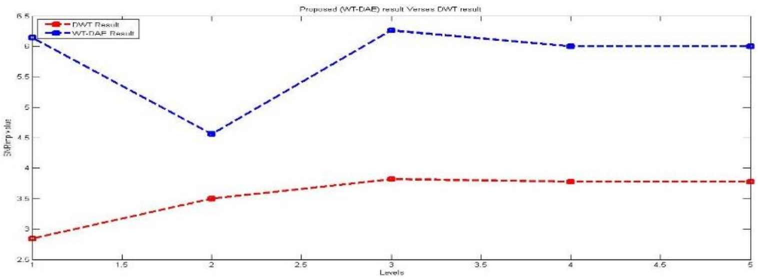

Fig. 10: SNR Imp Results of Proposed Method (WT-DAE) Compared with WT Result.

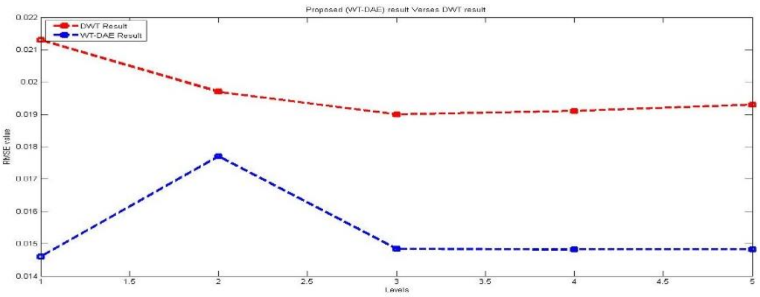

Fig. 11: RMSE Results of Proposed Method (WT-DAE) Compared with WT Results.

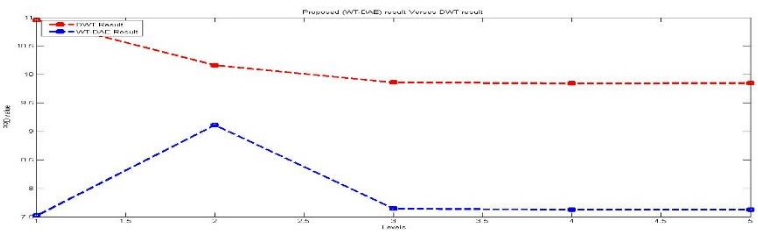

Fig. 12: PRD Results of Proposed Method (WT-DAE) Compared with WT Results.

Table 7: Result of Proposed Method with Different Levels

Level	MSE	RMSE	PRD	SNRimp
Level one	0.00029	0.017	8.764	4.82
Level two	0.00042	0.020	10.6	3.14
Level three	0.000337	0.0184	9.45	4.14
Level four	0.00038	0.0194	10.03	3.65
Level five	0.00039	0.0197	10.143	3.52

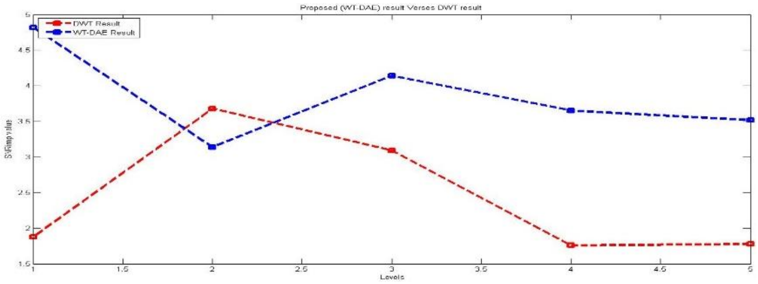

Fig. 13: SNR Imp Results of Proposed Method (WT-DAE) Compared with Db2 WT Result.

The comparison between use wavelet transform only by use db2 filter with the proposed method (WT-DAE) in terms of metrics are shown in figure (13), figure (14) and figure (15) for SNRimp, RMSE and PRD metrics respectively. The result show that better values of metrics are satisfied at level one and three while level two give the lowest results.

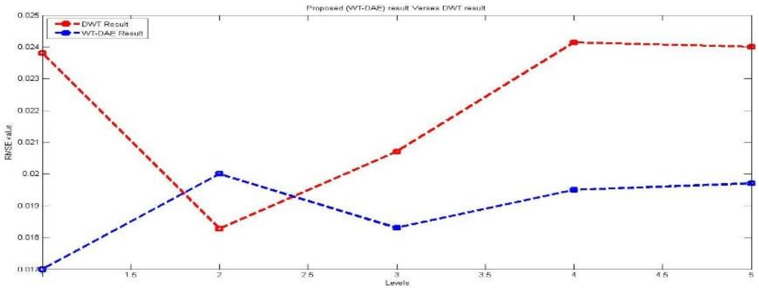

Fig. 14: RMSE Results of Proposed Method (WT-DAE) Compared with Db2 WT Result.

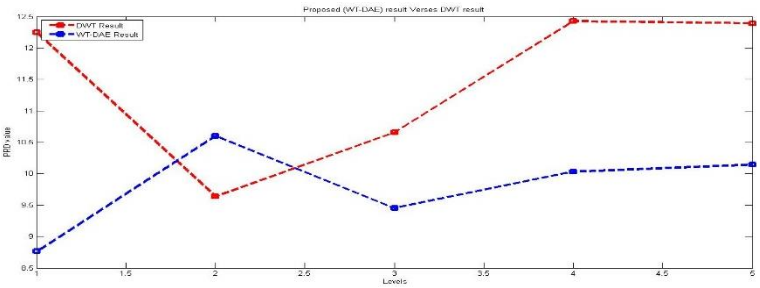

Fig. 15: PRD Values of Proposed Method (WT-DAE) Compared with Db2 WT Result.

6. Conclusion

In this paper, a new de-noising auto encoder based on discrete wavelet transform (WT-DAE) have been proposed for ECG signal de-noising to remove different types of noises from the signal. The proposed system is constructed from two stage, the first stage is based on using wavelet transform with threshold method , which is proposed to determine threshold value for thresholding the detail coefficient of wavelet transform to remove the details noise that is contained as high frequency component. Different metrics are used to evaluate the efficiency of the proposed system such as RMSE, MSE, PRD and SNR improvement. DWT was used with different levels and filter types and the result of the first stage show that , db4 filter give the best results among all other filter (3.82 dB in SNRimp) and this value is satisfied at level three of wavelet transform , while it is satisfied lower improvement at level one and level two (2.84 dB and 3.5 dB) respectively. For soft thresholding function, the best results are achieved by db6 filter (4.49 dB) at level three.
The second stage is accomplished by using a new DAE model. The proposed DAE was constructed from 14 layer, which are convolutional layers, max pooling layers, rectifier and up sampling and down sampling layers. The model training with MIT-BIH dataset (105938 signal) after augmented it by stretch and amplifying methods to increase the size of the data and increase the accuracy of the model. The model satisfied training loss $3.36*10^{-4}$ and validation loss $3.456*10^{-4}$, RMSE 5.996% and MSE was 0.000345. The model tested by test data (4000 signal). The results of the proposed DAE models show that, model1 achieved SNRimp values from (1.3 dB) to (2.9dB) for different signals, while model2 achieved from (1.19 dB) to (2.63 dB) in SNR imp values for the same signals. The result of the proposed system (WT-DAE) is (6.26 dB) at level three of wavelet transform and lowest value is (4.56 dB) at level two, Also there is high improvement in the values of SNR imp for the proposed method as compared with using wavelet transform only. The result show that the combined of the two previous method can increase the improvement of the performance.

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