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Convolutional Denoising Auto-Encoder Based AWGN Removal From ECG Signal

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***Abstract*—Electrocardiogram (ECG) signal is a non-invasive technique that is currently used to diagnose various types of cardiovascular diseases. However, ECG recording is vulnerable to different types of noises and artifacts that make it very difficult to obtain an accurate diagnosis. In this context, we propose a novel ECG denoising algorithm based on the deep Convolutional Denoising Auto-Encoder (CDAE) which requires minimal preprocessing steps, and conserves the important ECG features. In this study, the proposed CDAE algorithm is specifically implemented to remove the Additive White Gaussian noise (AWGN) from the recorded ECG signal. The CDAE was trained, validated and tested on a set of real ECG signals acquired from the well known MIT-BIH-Arrythmia (MITDB) database with artificially generated AWGN. The experimental results demonstrate that the proposed method shows better Signal to Noise Ratio (SNR) and lower Root Mean Square Error (RMSE) compared to some of the state-of-the-art methods. The promising results indicate also that the proposed CDAE technique is an effective solution for denoising the ECG signal, by providing ECG waves accentuation for other ECG processing applications like diseases diagnosis.**

***Keywords*—ECG signal, Denoising, Deep Learning, Convolutional Neural Networks, Convolutional Denoising Auto-Encoder**

I. Introduction

The Electrocardiography recording (ECG) is a graphical representation of heart's electrical activity. This is a fundamental medical tool that is widely used for diagnosis of heart diseases. ECG signal is recorded by placing a number of electrodes on some specific locations of person's body [1]. Generally, for a normal heart, ECG signal is pseudoperiodical and results in the appearance of five important waves (PQRST). The analysis of these features constitute a paramount step for improving diagnosis. Unfortunately, during acquisition of ECG signals, the latter are contaminated by various types of noises such as Electromyogram, Motion Artifacts and channel noise [2], which can affect severely the accuracy of diagnosis.

To deal with the problems of different types of these noises and artifacts, various denoising techniques have been proposed in the literature. Among those, classical FIR and IIR filters have been widely used [3]. However, the effectiveness of these methods is restricted due to the non-stationary nature of ECG. Therefore, adaptive filtering techniques such as Least Mean Square [4] were proposed. Nevertheless, these filters require an external reference signal. ECG denoising techniques in transform domain are proposed in numerous works like the Wavelet Transform [5], [6]. However, the latter technique has some limitations, such as the mother wavelet type selection, the decomposition level and others. Empirical Mode Decomposition (EMD) and its improved versions [7]–[9] have emerged as popular techniques and have shown successful denoising performances. However, the denoising capability of the developed algorithms lies on the difficulty to select effectively the Intrinsic Mode Functions to be rejected or thresholded. Recently, Deep Learning (DL) models have attracted more attention in different ECG signal processing tasks like heartbeats classification [10], [11]. In ECG signal denoising, a few number of DL works have been developed and the majority of them are mainly based on the Auto-Encoders [12]. Chiang et al. [12] have proposed an efficient algorithm based on the CDAE. They have tested their algorithm on real ECG signals taken from MITDB [13] corrupted with real noises taken from the MIT Noise-Test Stress Database. The proposed method [12] provides better performances compared to the conventional fully connected Deep Neural Networks (DNN) and Convolutional Neural Networks (CNN). Recently, Generative Adversarial Networks (GANs) have been applied by Singh et al. [14] to remove multiple types of noises from ECG signal. In this work, GANs have shown very promising results compared to the literature. In recent years, to detect arrhythmia and abnormalities using ECG, Tele-Cardiology diagnostic applications have attracted more interest. In such cases, the ECG data is transmitted through channels in order to be analyzed automatically in a remote center such e-health systems. However, poor channel conditions can add a channel noise to the ECG signal. This type of noise is commonly modeled by an AWGN [15]. To achieve an accurate diagnosis, removing this noise from ECG signal becomes a crucial task.

In this paper we propose a new ECG signal enhancement method based on the CDAE. The proposed algorithm can reconstruct the clean ECG signal from its noisy version using a novel Deep AE architecture. Hence, the resulted algorithm has been evaluated on the MITDB.

The remainder of this paper is organized as follows. Section II presents an overview on Denoising Auto-Encoder. Section III describes the proposed CDAE algorithm. The experimental results are given in Section IV. Section V concludes this work.

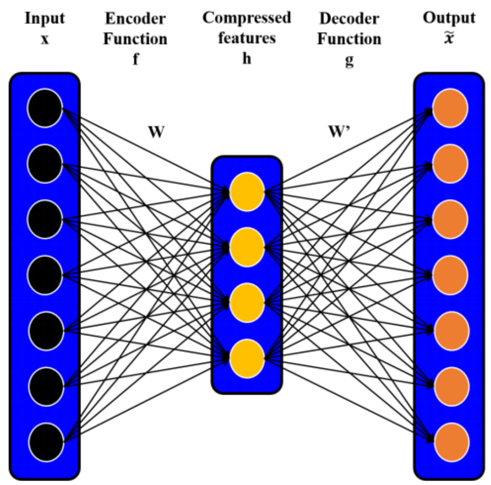

Fig. 1. Block diagram of a standard Deep AutoEncoder

II. Overview on Denoising Auto-encoder

In recent years, Auto-Encoders (AE) have been applied successfully for different applications [16], [17]. In this section, we introduce briefly a background theory about the AE and Denoising Auto-Encoders (DAE) architectures.

A. AutoEncoder

The Autoencoder is a special form of Neural Network (NN) which aims to generate a copy of the input at its output [18]. The major aim of an AE model is to reconstruct the input data with minimal representation. It contains generally two key parts: encoder and decoder. Fig. 1 depicts the basic diagram of a standard AE architecture which has three layers : input layer, hidden layer and output layer.

In Fig. 1, the encoder maps an input vector x to a latent low dimensional representation h using a non linear transformation f. The encoding process can be expressed as follows

$$h = encoder(x) = f(W.x + b) \tag{1}$$

where W and b are the encoder weights matrix and biases respectively. Then, the latent representation h is mapped to the final representation $\tilde{x}$ which has the same length as the input data x using a non linear transformation g. The decoding process can be expressed as follows

$$\tilde{x} = decoder(h) = g(W'.h + b') \tag{2}$$

where W' and b' are the decoder weights matrix and biases respectively. The biases b and b' are omitted in Fig. 2.

The parameters $\Theta = \{W, W', b, b'\}$ are determined by minimizing the reconstruction error between the input and the output data. The reconstruction error is described as a loss function, and the Mean Squared Error (MSE) is often used in the standard AEs as a loss function described as follows

$$J(\Theta) = \frac{1}{L}\sum_{i=1}^{i=L}(\frac{1}{2}||x_i - \tilde{x}_i||^2) \tag{3}$$

where L is the number of the training samples.

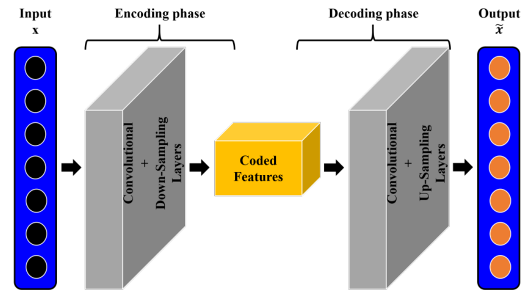

Fig. 2. Basic structure of a Convolutional AutoEncoder (CAE)

B. Denoising AutoEncoder

When the AutoEncoder is applied to reconstruct the original clean signal from its noisy version, it is termed a Denoising AutoEncoder (DAE). It is a sprecial type of AEs, which takes as input a corrupted version $\hat{x}$ of the noiseless data x. Then, it maps $\hat{x}$ to the corresponding latent representation $\hat{h}$ and subsequently to the reconstructed data $\tilde{x}$ in similar manner as shown in Fig. 1. Due to their powerful capabilities, AEs and DAEs have shown various applications including ECG heartbeats classification [18] and ECG data compression [17].

C. Convolutional Denoising AutoEncoder

Convolutional AutoEncoders (CAE) are another types of deep AEs which are based on the standard layers of Convolutional Neural Networks (CNN). Indeed, CAEs have the same basic structure of encoder and decoder as the conventional AEs, but they replace the fully-connected layers with convolutional ones. In general, the encoding process is achieved using a series of convolution and down-sampling layers. Then, a series of deconvolution and up-sampling layers are applied to decode the compressed features and ultimately to reconstruct the input data. Generally, the convolution and deconvolution layers are equipped with a non linear activation function such as the Rectified Linear Unit (Relu). Fig. 2 shows the basic structure of a classical model of a (CAE). Similarly to the traditional DAE, CDAE aims to recover the input signal x from its corrupted version $\hat{x}$. The standard DAE as well as the CDAE are trained using the noisy data $\hat{x}$ as input and the clean signal x as a target output. The MSE presented in (3) is the loss function that is often adopted also to train the CDAEs.

III. Proposed Methodology

A. ECG Database

In this study, we have evaluate the proposed CDAE algorithm over a various real ECG signals taken from the standard MIT-BIH Arrhythmia database [13]. This dataset contains 48 ECG recordings with 30 min duration sampled at 360 Hz (i.e. 650000 samples). Each of the ECG records is segmented into fragments with length of 3600 samples. Since a long duration ECG signals are used in this work, no additional step such QRS complex detection is required. A total of 180 fragments is constructed for each ECG record. Thus, the dataset used in this study contains 8640 fragments.

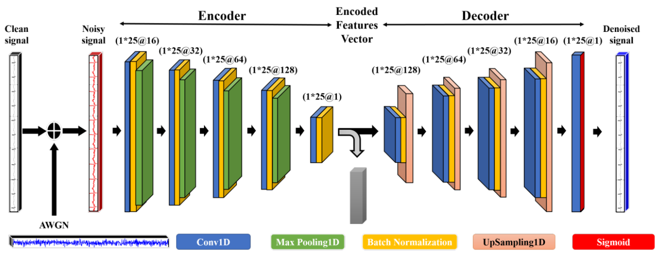

Fig. 3. Flowchart of the proposed CDAE algorithm for ECG noise reduction

B. Data Pre-processig

Before applying the proposed deep CADE model to denoise ECG data corrupted with an AWGN, the clean ECG fragments are normalized, such that the values of all input data sets are mapped into the ranges of $[0, 1]$. In this study, the Min-Max normalization was adopted as follows

$$x^{norm} = \frac{x - min(x)}{max(x) - min(x)} \tag{4}$$

where x and x^{norm} are the original clean ECG signal and its normalized version respectively.

C. Proposed CDAE Algorithm

The flowchart of the proposed CDAE model is depicted in Fig. 3. The encoding process consists of a stacked Convolutional and MaxPooling layers, while the decoding phase consists of a series of Convolutional and Up-sampling layers. The Convolutional layers in the encoder aim to extract the important features from the input data. After that, the Down-sampling operation, such as MaxPooling or AveragePooling, is applied to reduce the dimension of the feature maps. The result of the last Convolutional layer of the encoder part is a latent dimensional representation called: code or compressed features. The decoder part consists of two types of layers: Convolutional layers and Up-sampling layers. The Up-sampling layers work inversely to the Down-sampling layers. The output of the last layer of the decoder is a reconstructed version of the input clean ECG segment as shown in Fig. 3.

The proposed CDAE based ECG denoising consists of an encoder and a decoder with 27 layers in total. In the encoder section, the noisy signals with length of $(3600 * 1)$ are taken as the input of the model and the 1D convolution (Conv1D) process is applied on the first layer. After the convolution with 16 1D filters having length of 25 samples, batch normalization (BN) layer was used to normalize the activations of the previous layer for each batch [18]. The output feature maps of size $(3600 * 16)$ is then down-sampled by applying a maxpooling layer with a pooling size of 2 in this study, i.e., the output of the MaxPool1D layer is $(1800 * 16)$. Thereafter, the basic structure of $Conv1D + BN + MaxPooling1D$ is repeated three times with 32, 64 and 128 1D filters respectively having the same length as the first Conv1D layer. The last layer of the encoder comprises only a $Conv1D + BN$ layers, where a single filter of size $(1 * 25)$ is convolved with the extracted feature maps to obtain the encoded features having size of $225 * 1$. The details of the encoder part are given in Table. I.

The decoder section aims to decompresses the coded features with 225 samples to reconstruct the corresponding ECG segment. For this, the low dimensional coded features are passed through layers having a symmetric operation as the encoder part. Conv1D layer works in the same way as in the encoder part, while the Up-sampling layer is used to increment the size of the input feature maps. Hence, low dimensional features can be mapped to higher dimensional representation. For the output layer, a Conv1D layer with 1 filter of size $25 * 1$ is applied to produces the output denoised signal. In our model, each Conv1D layer is followed by a nonlinear activation Relu function, except the last layer where a sigmoid function is used. The details of the decoder part are given in Table. II.

IV. EXPERIMENTS

A. Performance Indicators

In the context of this work, the performance of the proposed CDAE algorithm is evaluated using the improvement in Signal to Noise Ration SNR (SNRimp) and the Root Mean Square Error (RMSE). SNRimp is defined as the difference between SNR after denoising (SNRout) and the original input SNR (SNRin). These metrics can be expressed as follows:

$$SNR_{imp}(dB) = SNR_{out} - SNR_{in} \tag{5}$$

$$SNR_{in}(dB) = 10 * log_{10}\left(\frac{\sum_{i=1}^{i=N} x_i^2}{\sum_{i=1}^{N}(\hat{x}_i - x_i)^2}\right) \tag{6}$$

$$SNR_{out}(dB) = 10 * log_{10}\left(\frac{\sum_{i=1}^{N} x_i^2}{\sum_{i=1}^{N}(\tilde{x}_i - x_i)^2}\right) \tag{7}$$

where N is the signal length.
The RMSE between the output denoised signal predicted by the model and the original clean signal is defined as follows:

$$RMSE = \sqrt{\frac{1}{N} * \sum_{i=1}^{N}(\tilde{x}_i - x_i)^2} \tag{8}$$

In eq. 6, 7 and 8, x represents the clean ECG segment, $\hat{x}$ the noisy ECG segment and $\tilde{x}$ the denoised ECG segment.

B. Experimental Setup

As mentioned above, ECG records from MIT-BIH Arrhythmia Database were used to evaluate the performances of the proposed model. Each ECG signal is transformed into 180 segments of length of 3600 samples. For each ECG record, the first 108 segments (60%) was used for train phase, the next 36 segments (20%) for validation phase and the last 36 segments (20%) for testing phase. In total, the dataset contains 8640 segments distributed as follows: 5184 segments for training, 1728 segments for validation and the remaining 1728 segments for testing the performances of the trained CDAE model.

To generate the noisy training, validation and testing sets, AWGN was added to the clean ECG segments. Training and validation data were corrupted with the same SNR of -4, -2,

TABLE I
DETAILS OF THE ENCODER SECTION LAYERS OF THE PROPOSED CDAE MODEL

No.	Layer	Kernel size	Number of Filters	Activation Function	Output Size
0	Input	-	-	-	3600*1
1	Conv1D	25	16	Relu	3600*16
2	BN	-	-	-	3600*16
3	Max-Pooling1D	-	-	-	1800*16
4	Conv1D	25	32	Relu	1800*32
5	BN	-	-	-	1800*32
6	MaxPooling1D	-	-	-	900*32
7	Conv1D	25	64	Relu	900*64
8	BN	-	-	-	900*64
9	MaxPooling1D	-	-	-	450*64
10	Conv1D	25	128	Relu	450*128
11	BN	-	-	-	450*128
12	MaxPooling1D	-	-	-	225*128
13	Conv1D	25	1	Relu	225*1
14	BN	-	-	-	225*1

TABLE II
DETAILS OF THE DECODER SECTION LAYERS OF THE PROPOSED CDAE MODEL

No.	Layer	Kernel size	Number of Filters	Activation Function	Output Size
1	Conv1D	25	128	Relu	225*128
2	BN	-	-	-	225*128
3	UpSampling1D	-	-	-	450*128
4	Conv1D	25	64	Relu	450*64
5	BN	-	-	-	450*64
6	UpSampling1D	-	-	-	900*64
7	Conv1D	25	32	Relu	900*32
8	BN	-	-	-	900*32
9	UpSampling1D	-	-	-	1800*32
10	Conv1D	25	16	Relu	1800*16
11	BN	-	-	-	1800*16
12	UpSampling1D	-	-	-	3600*16
13	Conv1D	25	1	Sigmoid	3600*1

2, 4, 6, 8 dB. For comparison with some existing works in the literature, testing data were corrupted with three different SNR levels of 0, 1.25 and 5 dB. We should to note that the added AWGN components are different between the three sets of training, validation and testing as well as in the same set. In this study, we adopted this scenario identically to real clinical environments where the recorded ECG signals and added noises are different.

The proposed CDAE algorithm based ECG denoising was created using the Keras library with Tensor-flow backend. In order to train, validate and test the proposed model, Google Colab systems with Graphical Processing Unit (GPU) were used. In this work, Adam optimizer with a learning rate of 0.001 was used to optimize the parameters of the model by minimizing the loss function. The learning phase was performed over 100 epochs using 64 batch sizes.

C. AWGN Elimination Using the Proposed CDAE

During the training phase of the proposed CDAE architecture, ModelCheckpoint and EarlyStopping functionalities of the Deep Learning Keras library was used to store the weights of the best trained model. Indeed, we keep only the weights of the training epoch that corresponds to the lowest MSE value on the validation set. Fig. 4 shows the loss curves of the learning process (i.e. on the training and validation sets) of the proposed CDAE over 100 epochs. It can be seen from this figure that the proposed model converges rapidly, and reaches a stable validation performances after 20 epochs approximately. Also, no over-fitting phenomena has been observed during the learning process of the proposed CDAE model. During the training phase of the proposed CDAE, the minimum MSE loss achieved for the denoised validation data was 0.0027, while the average loss for the noisy ECG segments was 0.0031.

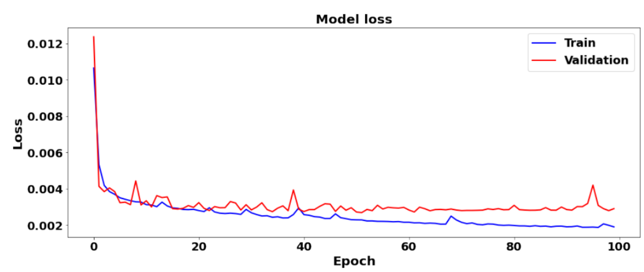

Fig. 4. The loss curves of training and validation performances of the proposed CDAE model

For visual assessment, Fig. 5 shows the experimental results of removing AWGN from a normal ECG segment. The first

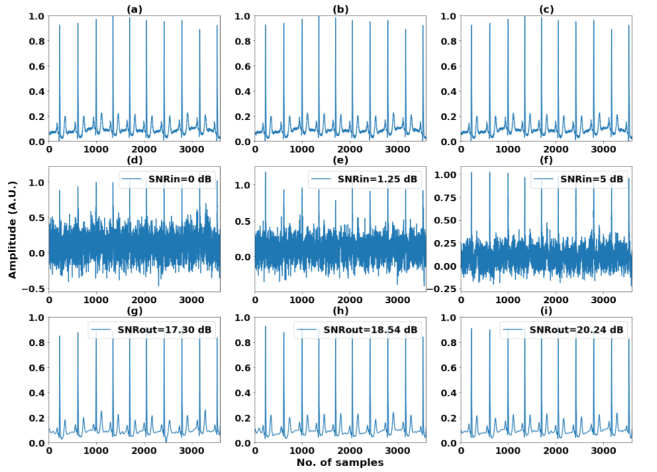

Fig. 5. Denoising results of the proposed CDAE algorithm for a corrupted normal ECG segment: (a),(b),(c) the original ECG signal-(d),(e),(f) the noisy ECG segments corresponding to $SNRin$ = 0, 1.25, 5 dB respectively-(g),(h),(i) the denoised ECG segments

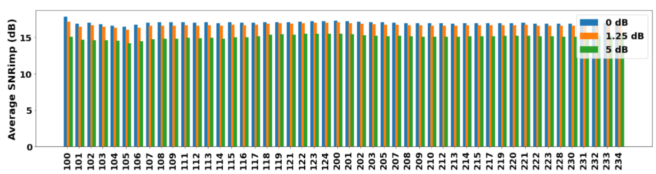

Fig. 6. Average $SNRimp$ denoising performances of the proposed CDAE model on the testing segments for all 48 ECG records at different input SNR levels of 0, 1.25, 5 (dB)

row for this figure displays the original clean segment. The middle row illustrates the noisy ECG segments for $SNRin = 0, 1.25$ and 5 dB respectively. The last row presents the denoising results obtained by the proposed CDAE algorithm. It can be seen from Fig. 5 that the artificial AGWN affect severely the important ECG features and specially P and T waves. However, the proposed CDAE can reconstruct clearly the ECG waveforms with minimal distortion compared to the original ECG segment. Indeed, for the three input $SNR(dB)$ values of $[0, 1.25, 5]$, CDAE algorithm can recover the original ECG signal with [$SNRimp$ of 17.30 dB, $RMSE$ of 0.021], [$SNRimp$ of 17.29 dB, $RMSE$ of 0.018] and [$SNRimp$ of 15.24 dB, $RMSE$ of 0.015] respectively.

The average performances in terms of $SNRimp$ and $RMSE$ of the trained CDAE model on the 36 testing ECG segments from each ECG record are shown in Fig. 6 and Fig. 7 respectively. In overall, in the testing data (i.e. $SNRin$=[0, 1.25, 5 dB]), the average SNR improvement and $RMSE$ values with the optimized CDAE model are [16.95 dB, 0.052], [16.69 dB, 0.049] and [15.25 dB, 0.035] respectively.

D. *Performances Analysis*

To the best of the authors knowledge, CDAEs have not been used to removes channel noise modeled as an AWGN from ECG signal in the literature. For example, in [12], the

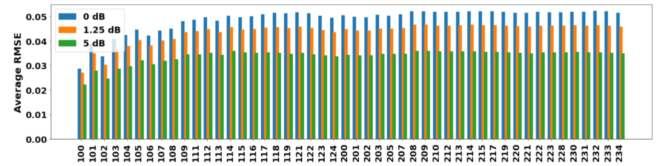

Fig. 7. Average $RMSE$ denoising performances of the proposed CDAE model on the testing segments for all 48 ECG records at different input SNR levels of 0, 1.25, 5 (dB)

developed CDAE model has been evaluated on real noises. Hence, the performance of the proposed method was compared only with respect to some alternative approaches based on signal processing tools including Wavelet Transform [5], Wavelet sub-band Thresholding [6], Stockwell-Transform [19] and the previous study based on the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and Hybrid Interval Thresholding (HIT) [9].

The proposed approach was tested over time segments from 10 ECG signals numbered: $'103.dat'$, $'105.dat'$, $'111.dat'$, $'116.dat'$, $'122.dat'$, $'205.dat'$, $'213.dat'$, $'219.dat'$, $'223.dat'$ and $'230.dat'$. These ECG data are taken by the Modified Limb Lead II (ML-II). For each ECG record, the proposed CDAE algorithm was tested on the last 36 segments extracted from this record. We should to note that these segments are not used in the training phase.

Table. III illustrates the denoising performances achieved by the different noise reduction methods in terms of $SNRout(dB)$ and $RMSE$ for the different input SNR values. In this table, the impressive performances are shown by using the italic boldface font. All values for comparison (i.e. $SNRout$ and $RMSE$) are taken from [19] and [9]. For our proposed CDAE model, the average $SNRimp(dB)$ and $RMSE$ values on the testing segments for each ECG record are taken as final results.

By analysing the content of Table. III, the four compared methods were found to provide minor improvements in terms of $SNRout(dB)$, and the proposed CDAE approach provides further enhancements. Indeed, for the three input SNR levels, the $SNRout$ values of the proposed model is significantly improved compared with other methods, which indicates that the proposed algorithm can filter noise more effectively.

Usually, lower $RMSE$ values is equivalent to better signal reconstruction. As can be seen in Table. III, compared to other existing WT-Soft, WT-Subband, ST transform and CEEMDAN-HIT methods, the proposed model achieves the minimum $RMSE$ values for all noisy environments. These results demonstrate that the proposed CDAE architecture can be used as an effective solution in reconstructing a denoised output signal from an original ECG in all noise levels as compared to the literature.

V. Conclusion

In this paper we evaluated the performance of ECG signal denoising using an end-to-end auto-encoder architecture

TABLE III

PERFORMANCE COMPARISON OF THE PROPOSED METHOD AGAINST SOME PUBLISHED RESULTS

Denoising Method	**SNRin**	**ECG Data**	**103**	**105**	**111**	**116**	**122**	**205**	**213**	**219**	**223**	**230**
WT-soft [5]	0dB	SNRout	5.84	7.35	7.04	6.63	6.69	5.45	5.91	7.25	7.35	5.73
		RMSE	0.511	0.429	0.445	0.466	0.463	0.534	0.507	0.434	0.429	0.517
	1.25dB	SNRout	6.72	7.96	7.72	7.37	7.47	6.31	6.62	8.02	8.1	6.44
		RMSE	0.461	0.400	0.412	0.428	0.423	0.484	0.467	0.397	0.394	0.476
	5dB	SNRout	9.66	10.22	9.62	9.65	9.77	8.57	8.74	10.36	10.87	8.85
		RMSE	0.33	0.308	0.33	0.329	0.325	0.373	0.366	0.303	0.286	0.361
WT-Subband [6]	0dB	SNRout	6.69	7.68	7.06	6.87	7.23	6.44	7.13	6.92	7.35	6.55
		RMSE	0.425	0.393	0.432	0.409	0.410	0.482	0.479	0.459	0.405	0.341
	1.25dB	SNRout	7.77	8.65	7.78	7.83	8.50	7.55	8.08	8.45	8.32	7.63
		RMSE	0.375	0.344	0.401	0.404	0.392	0.413	0.455	0.391	0.333	0.395
	5dB	SNRout	10.51	12.11	9.85	9.76	9.86	9.22	9.67	11.01	11.21	9.14
		RMSE	0.250	0.227	0.320	0.328	0.304	0.336	0.317	0.259	0.227	0.302
ST method [19]	0dB	SNRout	9.96	8.85	7.55	7.95	8.32	8.45	8.14	8.94	9.56	9.93
		RMSE	0.318	0.361	0.419	0.401	0.384	0.378	0.392	0.357	0.332	0.319
	1.25dB	SNRout	10.95	9.95	8.71	8.73	9.32	9.15	9.42	10.03	10.81	11.05
		RMSE	0.284	0.318	0.371	0.366	0.342	0.349	0.338	0.315	0.288	0.28
	5dB	SNRout	12.91	13.54	10.09	9.82	11.42	10.1	12.49	12.54	13.86	13.14
		RMSE	0.226	0.21	0.313	0.323	0.268	0.313	0.237	0.236	0.203	0.22
CEEMDAN-HIT [9]	0dB	SNRout	10.20	10.94	11.00	10.42	10.83	10.19	9.81	11.04	11.31	10.64
		RMSE	0.069	0.080	0.053	0.176	0.101	0.055	0.180	0.130	0.107	0.102
	1.25dB	SNRout	11.32	11.79	12.01	11.40	12.20	11.63	10.99	12.29	12.38	11.84
		RMSE	0.057	0.072	0.052	0.047	0.100	0.050	0.152	0.113	0.090	0.089
	5dB	SNRout	14.00	15.62	14.60	15.23	14.21	14.58	14.50	15.28	15.74	14.70
		RMSE	0.040	0.049	0.035	0.329	0.069	0.069	0.107	0.080	0.060	0.064
Proposed Method	0dB	SNRout	***16.79***	***16.45***	***17.1***	***17.04***	***17.16***	***17.06***	***16.98***	***16.95***	***16.90***	***16.88***
		RMSE	***0.041***	***0.047***	***0.049***	***0.050***	***0.051***	***0.050***	***0.052***	***0.052***	***0.052***	***0.052***
	1.25dB	SNRout	***17.69***	***17.31***	***17.95***	***17.95***	***18.23***	***18.02***	***17.94***	***17.92***	***18.87***	**17.83**
		RMSE	***0.036***	***0.040***	***0.044***	***0.045***	***0.045***	***0.045***	***0.046***	***0.046***	***0.046***	***0.046***
	5dB	SNRout	***19.60***	***19.21***	***19.98***	***20.04***	***20.50***	***20.17***	***20.19***	***20.21***	***20.14***	***20.11***
		RMSE	***0.029***	***0.032***	***0.034***	***0.035***	***0.035***	***0.035***	***0.036***	***0.035***	***0.035***	***0.035***

composed of a Convolutional Neural Networks (CNN). This method takes advantage of Denoising Auto-Encoder (DAE) to reconstruct successfully the clean ECG signal from its noisy version. The proposed algorithm is tested on real ECG signals taken from MITDB. This study has been focused only on the channel noise which is modeled by an AWGN. The proposed CDAE outperforms some exising works in the literature in terms of the SNR improvement and RMSE.

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