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Adversarial de-noising of electrocardiogram

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ABSTRACT

The electrocardiogram (ECG) is an important index to monitor heart health and to treat heart diseases. The ECG signals acquisition process is often accompanied by a large amount of noise, which will seriously affect the doctor's diagnosis of patients, especially in the telemedicine environment. However, existing de-noising methods suffer from several deficiencies: (1) the local and global correlations of ECG signals are not considered comprehensively; (2) adaptability is not good enough for various noise; (3) severe distortion in signals may be triggered. In this paper, we propose an adversarial method for ECG signals de-noising. The method adopts a newly designed loss function to consider both global and local characteristics of signals, utilizes the adversarial characteristics to accumulate knowledge on the distribution of ECG noise continuously through the game between the generator and the discriminator, and evaluates the quality of de-noised signals against SVM algorithm. The extensive experiments show that compared to the state-of-the-art methods, our method achieves up to about 62% improvement on the SNR of de-noised signals on average. Evaluations on the quality of de-noised signals imply that our method can effectively preserve useful medical characteristics of ECG signals.

1. Introduction

1.1. Motivations

Among the various health-threatening diseases, heart diseases have become a major public health issue with high morbidity and mortality, which has posed a heavy burden on the society. An electrocardiogram (ECG) is bioelectrical changes produced by a heart during the cardiac cycle and can be detected on the body surface by specialized devices. The ECG is an important index used to detect [1], classify [2] and treat heart diseases.

With the development of Internet of Things (IoT) [3,4] and cloud computing [5–7], telemedicine has gradually been applied in hospitals, especially the application of remote ECG monitoring system [8], which allows to monitor patients' heart health in real time at home and to transmit sensor data to doctors at hospitals. This remote ECG monitoring system can produce dynamic ECG signals and monitor the condition of patient in a real-time manner. Compared with static ECG signals collected in the strict-regulated medical environments of modern hospitals, such dynamic ECG signals are often accompanied by different types of noise due to complicated acquisition environments. It is notable that the noise can interfere with the doctor's diagnosis and may cause ECG signals to lose medical value. The medical value refers to the characteristic information contained in the signal itself, which doctors can use to diagnose the health of the heart. Therefore, it is of great significance to de-noise the raw ECG signals.

ECG signals generally include three main types of noise: the electrode motion artifact (EM), the muscle artifact (MA), and the baseline wander (BW). The EM noise in ECG signals is mainly caused by the 50Hz power line interference as well as by high harmonic interference, the interference amplitude to ECG signals is typically between 0–50%. The MA noise is mainly caused by the contraction of human muscle cells. Studies have determined that there is a skin potential of 30mV in the outer epidermis, which interferes with the acquisition of ECG. As for the BW noise, its frequency is very low and its main component is around 0.1Hz. Once the ECG signals are seriously interfered by noise, such as in telemedicine environments, they cannot be effectively utilized and

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even completely lose their value, which is extremely detrimental to the diagnosis of heart diseases.

Researchers have done a great deal of work in the field of ECG noise reduction. Traditional methods of ECG de-noising include spectral decomposition [9], Fourier decomposition [10], filter [11], Empirical Mode Decomposition (EMD) [12–14], Wavelet Transform (WT) [15,16] and so on. These methods may achieve satisfactory results on certain types of ECG, but they have the following disadvantages: (1) the local and global correlations of ECG signals are not considered comprehensively; (2) adaptability is not good enough for various noise; (3) severe distortion in signals may be triggered.

The adversarial method (mainly manifested as Generative Adversarial Network (GAN)) is a popular thought in the field of deep learning in recent years. The method learns data characteristics by min-max game between the generator and the discriminator. It not only has high flexibility, but also can learn the whole distribution characteristics of samples from limited data. Similarly, for noise reduction, it is possible to learn the overall distribution of noise and then to obtain a model with high adaptability through adversarial method. Due to these reasons, we believe that the adversarial method is a very promising method for noise reduction.

1.2. Our contributions

First, we establish a new view on the adversarial method, i.e., the adversarial method has the ability to learn the difference between the input and the output. Thanks to the point of view, it makes possible de-noising ECG signals with the adversarial method. In our opinion, the view can effectively promote the further applications of the adversarial method.

Second, we propose a new loss function that acts as a more effective alternative for getting high quality signals. Two extra parts are added to the newly designed loss function. The first part is the distance function (Eq. (4)), which is used to capture the global characteristics of signals and to make the training process stable. The second part is the maximum difference function (Eq. (5)), which is used to capture the local characteristics of signals and to preserve the useful medical characteristics of signals.

Third, we propose an adversarial de-noising method of ECG signals. Focusing on the time domain characteristics of ECG signals, the method utilizes the adversarial thought to accumulate knowledge on the distribution of ECG noise continuously through the game between the generator and the discriminator.

Last, we evaluate the de-noised ECG signals qualitatively by Support Vector Machine (SVM) algorithm. The extensive experiments show that the classification accuracy of the de-noised signals using our method are almost as high as that of clean signals. It implies that our de-noising method can effectively preserve medical characteristics.

To the best of our knowledge, our method achieves the state-of-the-art result on removing the noise of ECG signals, including the EM noise, the MA noise as well as the BW noise. We are the first to evaluate the medical value of de-noising ECG signals qualitatively. Our work has two significance: on one hand, it can save doctors' time of reading ECGs and greatly reduce the burden of their work. On the other hand, it is of great significance to the development of telemedicine.

The overall structure of this paper is organized as follows. Section 2 describes the related work. Section 3 formally describes the ECG de-noising problem. In section 4, we introduce our adversarial de-noising method of ECG signals in detail. Section 5 describes the experimental data, the specific process of the experiment and the results. The last section summarizes the full paper of the work.

2. Related work

Currently, noise reduction methods of ECG signals can be mainly divided into two categories: the traditional de-noising methods and the deep de-noising methods.

There are numerous traditional methods of ECG de-noising, such as spectral decomposition [9], Fourier decomposition [10], filter [11], Empirical Mode Decomposition (EMD) [12–14], Wavelet Transform(WT) [15,16] and so on. The filter method for ECG signal de-noising can be divided into various kinds, such as Kalman filter [17], FIR filter [18], IIR filter [19] and filter banks. The EMD method [20] decomposes the signal into a series of Intrinsic Mode Functions (IMF) and possesses adaptability characteristics. The Wavelet transformation is the process of decomposing and reconstructing a signal utilizing the wavelet basis formed by wavelets dilation and translation. Ider et al. proposed a method to reduce the line interference from electrocardiograms [21]. However, the traditional methods of noise reduction does not fully consider the local and global correlations of the ECG signals, and does not have good adaptability. Consequently, they are not able to effectively remove the noise in ECG signals and may cause distortion in de-noised signals.

With the development of deep learning, neural networks have been widely utilized in ECG de-noising. Dey et al. proposed a functional link artificial neural network (FLANN) for the BW noise reduction [22]. Based on feed forward neural networks with three hidden layers, Rodrigues et al. conducted de-noising experiments on ECG signals only containing the EM noise and achieved good results. Poungponsri et al. [23] proposed a wavelet neural network (WNN) de-noising method, which combines the multi-resolution characteristic of the wavelet and the adaptive learning characteristic of the neural network. It is notable that WNN can effectively reduce the interference of white noise in the ECG. However, few methods focused on the diversity and complexity of the ECG noise. Suranai made improvements to WNN in his later work, which was able to effectively reduce the EM, the MA and the BW noise in ECG signals. Additionally, Peng et al. combined a de-noising Auto Encoder (DAE) network and its improved version with wavelet transform, which was able to effectively reduce the three kinds of noises in ECG signals [24].

In summary, the traditional methods of noise reduction do possess certain limitations and cannot satisfy the need of ECG signal de-noising. The Fourier transform can reveal the correlation of signals in the time and frequency domain, but the Fourier transform must analyze signals as a whole, therefore it cannot meet the requirements of real-time and local analysis of ECG signals. The filter methods can get rid of noise to some degree, but the effect is sometimes not good enough and the ECG de-noised signals may lose their medical value. Compared with the Fourier transform method, the wavelet transform has good locality properties in both time and frequency domain, but the wavelet transform has no good adaptability. Additionally, it is also notable that neural networks have been widely used in noise reduction, such as FLNN, WNN and DAE. However, FLNN and WNN can only remove one kind of noise in ECG signals, and is not able to reflect the complex and diversity characteristics of noise. Although the improved WNN and DAE are able to remove three kinds of noise in ECGs, it can cause ECG signals to lose medical value.

The adversarial method is a popular thought in the field of deep learning in recent years. Researchers have made a lot of improvements on it, such as the Conditional GAN [25], the Wasserstein GAN [26] and the Cycle GAN [27]. There are many studies utilizing GAN models for noise reduction. Divakar and Zhou did a lot of work in image de-noising by utilizing the idea of GAN respectively [28,29]. Wolterink et al. employed the GAN model to reduce noise in the low dose CT and get good results [30]. Yi [31] and

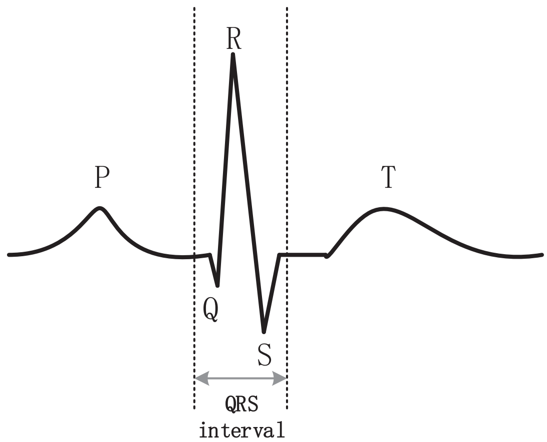


Fig. 1. A cycle of ECG waveform.

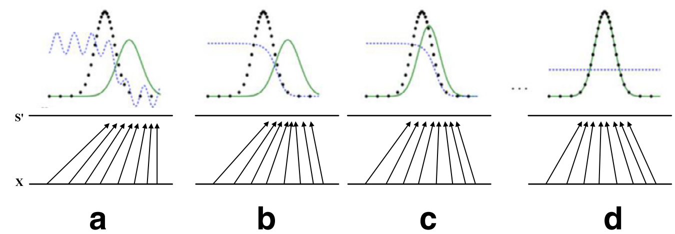


Fig. 2. The adversarial learning process of GAN model. Like the original GAN paper [33], (a) consider an adversarial pair near convergence: P_g is similar to P_{data} and the discriminator is a partially accurate classifier. (b) Then the discriminator is trained to distinguish the de-noised ECG signal from the original clean ECG. In (c), the discriminator constantly guides the generator to approach the distribution of the original clean ECG data. In (d), after enough steps of training, if the generator and the discriminator have enough capacity, they will reach a point at which both cannot improve because $P_g = P_{data}$.

Yang [32] chose the model based on the CGAN model and its improved version to de-noise low dose CT. However, most of them are limited to image data, and the reason why GAN can be used as a noise reduction method has not been discussed at all. As mentioned above, we apply the adversarial method to the noise reduction problem of ECG signals in this paper.

3. Problem

Fig. 1 depicts a period of the ECG waveform, which generally includes several different characteristic waves, such as P wave, QRS complex and T wave. Every wave represents significant meaning during a cardiac cycle. Doctors diagnose the condition of patients mainly according to the shape change of these characteristic waves. However, the collection of ECG signals is not entirely accurate and often contains various noise, which may affect the doctor's diagnosis and constrain the medical value of ECG signals, especially in the telemedicine environment.

As we know, the de-noising problem can be formally described as

$$X(t) = S(t) + N(t), t \geq 0 \tag{1}$$

where $X(t)$ is noisy signals, $S(t)$ is useful signals and $N(t)$ is the noise. The objective of de-noising is to suppress noise $N(t)$, thereby separating useful signals $S(t)$ from noisy signals $X(t)$. Since ECG signals are sampled by devices, so we can deduce the equation

$$S[i] = X[i] - N[i], i = (0, 1, 2, \ldots) \tag{2}$$

according to Eq. (1), where $X[i] = (x_1, x_2, \ldots, x_k)$, $S[i] = (s_1, s_2, \ldots, s_k)$, $N[i] = (n_1, n_2, \ldots, n_k)$ are all one-dimensional vectors and represent noisy signals, useful signals and the noise, i represents the number of samples and k represents the length of one sample, respectively. The purpose of ECG noise reduction is to obtain high quality useful signals $S[i]$ from the noisy signals $X[i]$.

4. Method

4.1. The overall structure

As mentioned above, GAN is a popular deep neural network model proposed by Ian GoodFellow [33]. It comprises two main parts: a generator and a discriminator. The generator generates fake samples close to the real from random input; while the discriminator aims to differentiate between the real and the fake generated by the generator.

It is generally believed that GAN is a generative model, which is able to generate plausible data with random input. i.e., GAN has the ability to learn the essential characteristics of the target data. Since the input of GAN is random data, it can also be understood that GAN has the ability to learn the difference between the input and the output. We utilize the figure in [33] (Fig. 2) to make a more graphic statement of this new view. X is the noisy data and S' is the de-noised ECG data generated by the generator. The green line represents the distribution of the de-noised ECG data and the black dotted line depicts the distribution of the original clean ECG data. The blue dotted line denotes the discriminator. We define P_g as the generator's distribution over data S' and P_{data} as the distribution over the original clean data. After enough steps of training, if the generator and the discriminator have enough capacity, they will reach a point at which both cannot improve because $P_g = P_{data}$. In our study, this means that the distribution of de-noised signals equal to the distribution of the original clean signals. It also means that the generator have learned the difference between the noisy signal and the clean signal, which is exactly what we expect—the characteristics of the noise, because the generator take the noisy signal as input and the clean signal as the output.

Our method also comprises two main parts: the generator and the discriminator. The generator takes the raw noisy ECG signals as input and then generate the de-noised ECG signals. The discriminator aims to differentiate between the de-noised ECG data generated by the generator and the original clean ECG data. Through the adversarial training between the generator and the discriminator, the generator continuously learns the difference between the input signals and the orginal clean signals, which is exactly the characteristics of noise. When the losses of the generator and the discriminator no longer fall and are within a reasonable range, the generator will obtain the capability of noise reduction. The overall structure of the proposed method is shown in Fig. 3.

4.2. Loss function

As described in Section 3, the ECG noise reduction aims to suppress the N and to get the corresponding useful ECG signals S from the noise-containing ECG signals X. Assuming that the generator network is a function $G(x)$ and the generated de-noised ECG signals is $S' = \left(s'_1, s'_2, \ldots, s'_k\right)$, the generator of adversarial de-noising can be described as $S' = G(X)$. Due to the ability of learning the difference between the input and the output (Section 4.1), GAN can learn the distribution characteristics of the noise and generate the de-noised ECG signal S' by inputting an noisy ECG signal X. We want that the closer S' is to S, the better. i.e.,

$$G(X) = S' \quad \overrightarrow{a.c.a.p} \quad S = X - N, \tag{3}$$

where a.c.a.p is an abbreviation of "as close as possible".

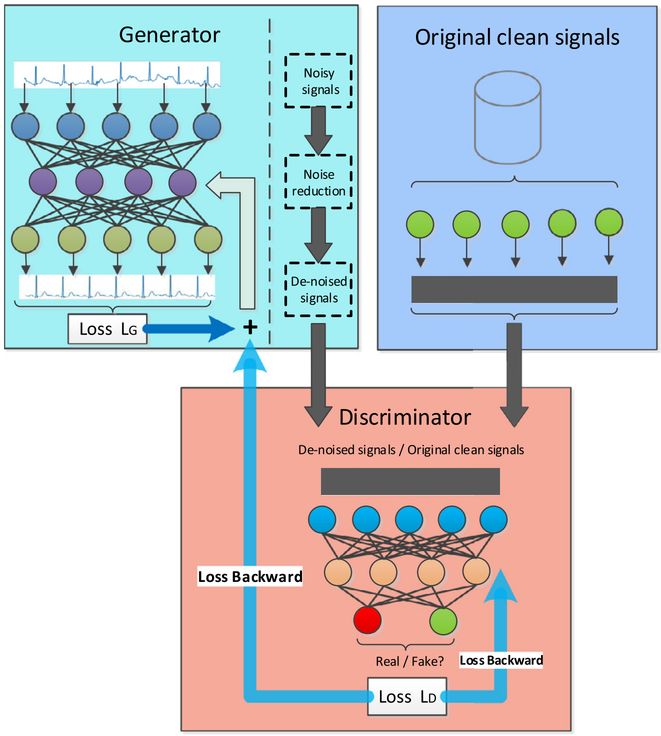


Fig. 3. The overall structure of the proposed method.

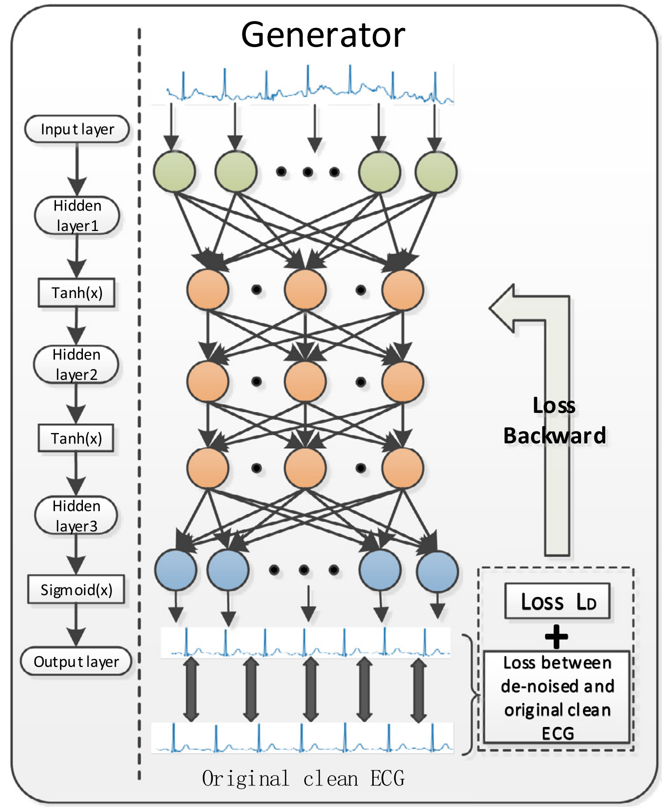


Fig. 4. The generator network.

It can be seen from Eq. (3) that the smaller the difference between S' and S, the better the de-noised signals obtained. So the distance function

$$l_{dist} = \sqrt{\sum_{k=1}^{K} \left|s'_k - s_k\right|^2} \tag{4}$$

is added to the generator's loss function. It means the difference of all the sampling points between S' and S as a whole. It also can be regarded as the global difference characteristics between S' and S.

The local characteristics of ECG signals may have high medical value. In order to preserve the local features, the maximum local difference between S' and S

$$l_{max} = max(|s'_1 - s_1|, |s'_2 - s_2|, \ldots, |s'_k - s_k|) \tag{5}$$

is added to the generator's loss function, too. It means the maximum difference of individual sampling point pair between S' and S. It also can be regarded as the local difference characteristics between S' and S. Indeed, it also represents the maximum local error that needs to be suppressed when GAN reduce the noise during the training process.

Then the loss function L_G of the generator is defined by

$$L_G(\Theta) = l_{real} + \lambda l_{dist} + \beta l_{max}, \tag{6}$$

which consists of three parts: l_{real}, l_{dist} and l_{max}, where

$$l_{real} = \log\left(1 - D_\psi(G_\theta(X))\right) \tag{7}$$

is the adversarial loss of the generator, l_{dist} and l_{max} are the distance and the maximum local difference between S' and S respectively described above, λ and β are the corresponding weights. In Eq. (7), $G_\theta(X)$ indicates the de-noised signal generated by the generator with parameters of θ, which takes the noisy ECG signal X as input. $D_\psi(G_\theta(X))$ indicates the probability evaluated by the discriminator that $G_\theta(X)$ come from original clean ECG signals rather than de-noised signals.

We take the original loss function defined in [27] as our discriminator's loss function

$$L_D(\Psi) = -\left[\log\left(D_\psi(S)\right) + \log\left(1 - D_\psi\left(G_\theta(X)\right)\right)\right], \tag{8}$$

where $D_\psi(S)$ represents the probability evaluated by the discriminator that S come from original clean ECG signals. The model train discriminator to maximize the probability of assigning the correct label to both original clean signals and de-noised signals produced by the generator. In other words, the generator tries to maximize the value of $D_\psi(G_\theta(X))$ and the discriminator tries to minimize the value of $D_\psi(G_\theta(X))$.

Taken together, the generator passes the loss of the discriminator to make the de-noised ECG signal distribution constantly approaching the original clean signal distribution. By adding the loss function L_G with the distance function and the maximum difference function, the generator can continuously learn both global and local characteristics of the noise distribution in noisy ECG signals, while making the de-noised ECG signal keep the characteristics of the original clean signal as much as possible.

4.3. Adversarial de-noising method

Figs. 4 and 5 depict the network structure of the generator and discriminator, respectively. The generator contains three hidden layers. Each layer takes the previous layer's output as input and then computed by function

$$y = f\left(\sum_{k=1}^{M} w_k x_k - b\right)$$

to generate data for the next layer, where $f(x)$ is an activation function and M indicates the length of the previous layer's output

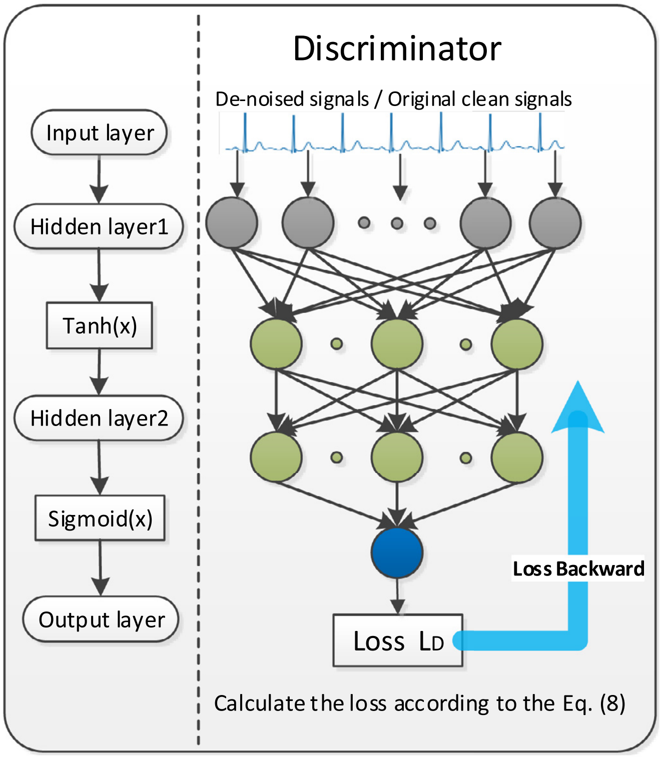


Fig. 5. The discriminator network.

vector. The activation function of the first two layers is

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}},$$

while the output layer is sigmoid function

$$S(x) = \frac{1}{1 + e^{-x}}.$$

Firstly, the noisy ECG signal X passes through the generator network and outputs the de-noised ECG data S'. The discriminator contains two hidden layers and takes the original clean ECG data S and the de-noised data S' generated by the generator as input data. Each type of data is calculated by function

$$y = f\left(\sum_{k=1}^{M} \xi_k s_k - \delta\right).$$

Then, the discriminator generates a probability value with sigmoid function, which indicates the probability that the input data is not a generated signal. We define $\Theta = (w_k, b)$ and $\Psi = (\xi_k, \delta)$ as the parameters of the generator and the discriminator correspondingly.

In the course of training, the goal of the discriminator is to decrease the probability value of $D_\psi(G_\theta(X))$ and increase the probability value of $D_\psi(S)$. On the contrary, the generator aims to increase the probability value of $D_\psi(G_\theta(X))$, which evaluated by the discriminator. In other words, the purpose of the discriminator is to improve the ability to differentiate between the original clean data and the generated data, and the generator tries to be as close to the original clean data as possible to cheat the discriminator. Through the two-player minimax game, the generator and the discriminator constantly updated their parameters, and finally the generator network obtained with the ability of noise reduction.

5. Results and discussion

5.1. Experimental setup

Experimental configuration: We conduct our experiments on a workstation, which has two 12-core Intel Xeon(R) E5-2673 v3 processors with 64GB DRAM and one GeForce GTX 1080 Ti GPU. All experiments are run on the operating system of Ubuntu 16.04. We implement our codes in the deep learning framework of pytorch 0.3.0.

Performance metrics: The performance evaluation of our experiment is based on the root mean square error (RMSE) and the signal-noise ratio (SNR), which are defined in the following:

$$RMSE = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(s'_k - s_k\right)^2} \tag{9}$$

and

$$SNR = 10\ \lg \frac{\sum_{k=1}^{K}\left(s_k\right)^2}{\sum_{k=1}^{K}\left(s'_k - s_k\right)^2}, \tag{10}$$

where s_k is the original clean ECG signal, s'_k is the ECG signal after de-noising, and K is the number of sample points. RMSE describes the difference between the two types of data, that is, the degree of proximity. The smaller the RMSE value, the smaller the difference between the data. SNR represents the ratio of the signal to the noise contained in the signal. The larger the SNR value, the better the noise reduction effect.

What's more, we take Support Vector Machine (SVM) algorithm as another metric to qualitatively evaluate the de-noised ECG signals. In the telemedicine environment, the signal processing generally includes the following steps: acquisition, noise reduction, and classification. The classification of ECG signals is an important step in detecting heart disease. The quality of noise reduction will directly affect the accuracy of classification. Therefore, we evaluate the quality of the de-noised signal by classifying the signals. SVM is a common and standard classification method, which has stable classification results and good interpretability. In contrast, the classification results of the deep neural network model are related to the network structure and training process (e.g. hyper-parameters, etc.), and the interpretability of the deep neural network model is black-box. To sum up, it is appropriate to select SVM algorithm as a standard method for evaluating signal quality after noise reduction.

Datasets: We utilized the MIT-BIH Arrhythmia Database [34] as well as the MIT-BIH Noise Stress Test Database [35] in PhysioBank [36] as experimental datasets. The MIT-BIH Arrhythmia Database is randomly selected from clinical medical data of Boston's Beth Israel Hospital. It contains a total of 48 records and each record includes a modified limb lead II (MLII) and lead V1 (occasionally V2 or V5) signals. In addition, we selected the EM, BW and MA noise record from the MIT-BIH Noise Stress Test Database as noise data, representing the three main types of the ECG noise. These records are collected from volunteers by the professional ECG acquisition devices. The length of each record is 30 minutes and the sampling frequency is 360 Hz. By setting different SNRs, we add the noise data to the original ECG signal to produce the training and test data for the following experiments. As the ECG signal has a certain periodicity, it is appropriate to divide the signal record and utilize the signal in a heartbeat period as a training sample. Considering the learning characteristics of the neural networks, the ECG signal samples are normalized by Min-Max normalization as follows:

$$Normalized(x_k) = \frac{x_k - x_{min}}{x_{max} - x_{min}}, \tag{11}$$

where x_{min} and x_{max} represent the maximum and the minimum values of x respectively.

Table 1
The average SNR and RMSE of de-noising results with different loss functions.

Added loss function	The average SNR	The average RMSE ($\times 10^{-2}$)
Default loss function	14.16	7.889
Mean Square Error (MSE)	31.95	1.054
Distance function	32.99	0.986
Distance function + Max difference	32.48	1.004
Cross training with Distance function and Maximum difference	**33.02**	**0.944**

Training parameters: We employed the generator network structure as 310-250-250-250-310. The discriminator network is implemented by a fully connected network containing two hidden layers, and its network structure is 310-150-150-1. In experiments, the number of the training samples for each type of noise is 54,000 and the test samples is 5940. The generator and the discriminator networks parameters are simultaneously optimized using the Adam optimizer with the learning rate of 0.0001.

5.2. Evaluation of loss function

This experiment compares the noisy reduction performance of different loss functions, which are introduced in Section 4.2. The ultimate loss function comprises 3 parts, l_{real}, l_{dist} and l_{max}. For comparison purpose, the loss of mean square error (MSE)

$$l_{mse} = \frac{1}{K}\sum_{k=1}^{K}\left(s'_k - s_k\right)^2 \tag{12}$$

is introduced. We evaluate 4 combinations of them in the generator's loss function as follows:

- l_{real}
- $l_{real} + \lambda l_{mse}$,
- $l_{real} + \lambda l_{dist}$,
- $l_{real} + \lambda l_{dist} + \beta l_{max}$,
- $l_{real} + \lambda l_{dist} + \beta l_{max}$, with 2 stages training.

The fifth combination refers to train the GAN with $l_{real} + \lambda l_{dist} + \beta l_{max}$ in the first stage and then train the model with $l_{real} + \lambda l_{dist}$ in the second stage. In our experiments, we choose $\lambda = 0.7$ and $\beta = 0.2$ correspondingly.

Table 1 shows the SNR and RMSE of de-noising results on average with different loss functions. The distance function tend to perform little better than the MSE function. An additional max function may slightly affect the result of both SNR and RMSE. But if using 2 stages training, the combination of an additional max function achieves the best performance on both SNR and RMSE.

Fig. 6 presents the de-noised signals of different loss functions. In each line, the right subfigure is the details of signals in the red box on the left subfigure. The default adversarial loss function (Fig. 6a) achieves bad results, while the remaining 4 loss functions achieve satisfactory results. The distance function tend to perform little better than the MSE function (Fig. 6b and c). What stands out in this figure is that the characteristic that the second protrusion is higher than the first protrusion can be learned by adding an additional max function (Fig. 6d and e). It implies that an additional max function can make the de-noising signals more closer to the original clean ECG signals. However, straightly adding the max function makes waveforms unsmooth (Fig. 6d), that is, there are many burrs in the details of the de-noised signals. Through 2 stages training, the waveforms become smooth and the useful characteristics are preserved(Fig. 6e).

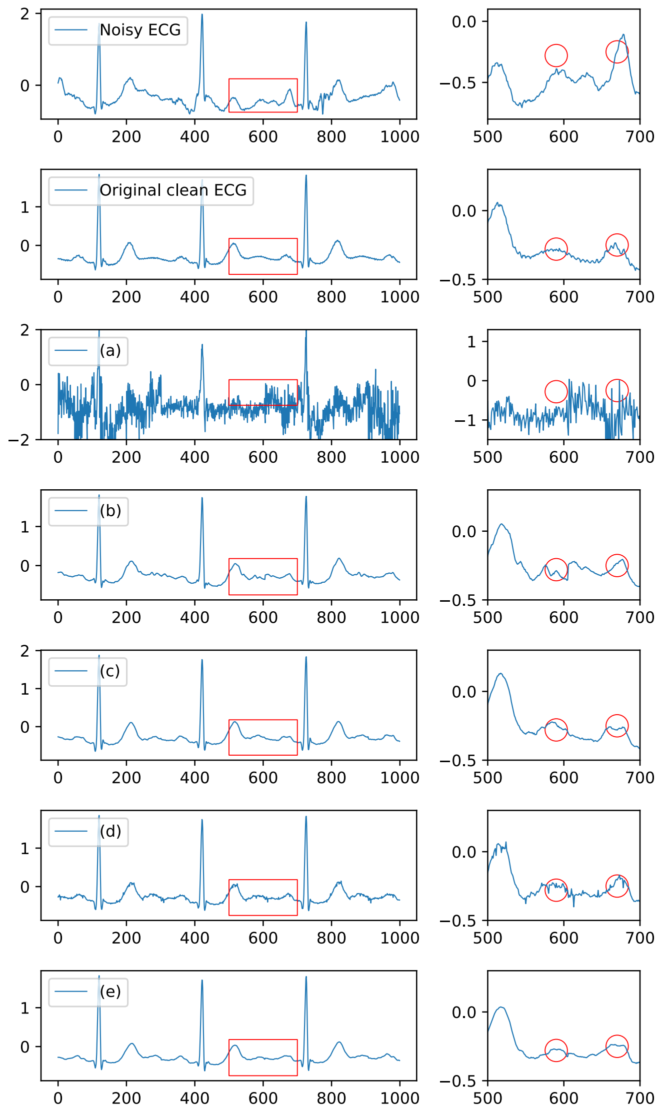


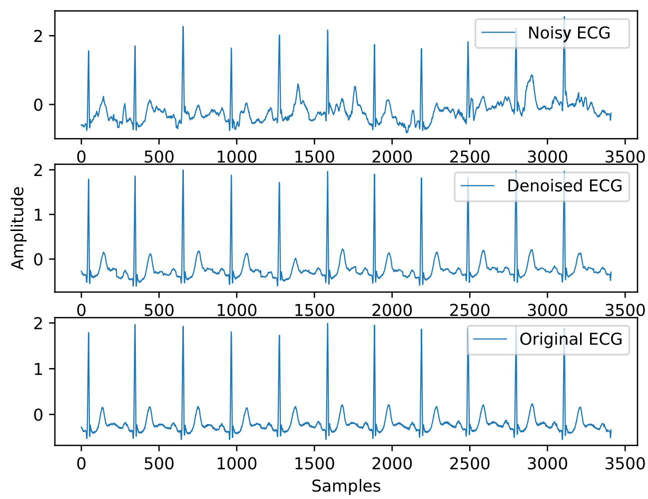
Fig. 6. The comparison of noise reduction results with different loss functions. The upper portion of the figure represent the noisy ECG and the original clean ECG respectively. The sub-picture (a) depicts the de-noised results using the default loss function of the generator. (b) shows the de-noising result using the loss function of mean square error. (c) displays the de-noised results utilizing the distance function. (d) combines the distance function and the local maximum difference to de-noise the ECG signals. (e) shows the results of using the loss of distance function and local maximum difference with 2 stages during the training process, which uses two functions in the first stage and use the distance function to fine-tune the results in the second stage. We magnify the part marked by the red box and draw it in the right of every sub-picture correspondingly. Meanwhile, two main protrusions are labeled by red circle at the same positions of original clean ECG signals in magnified ECG waveform.

To summarize, the following observations can be drawn:

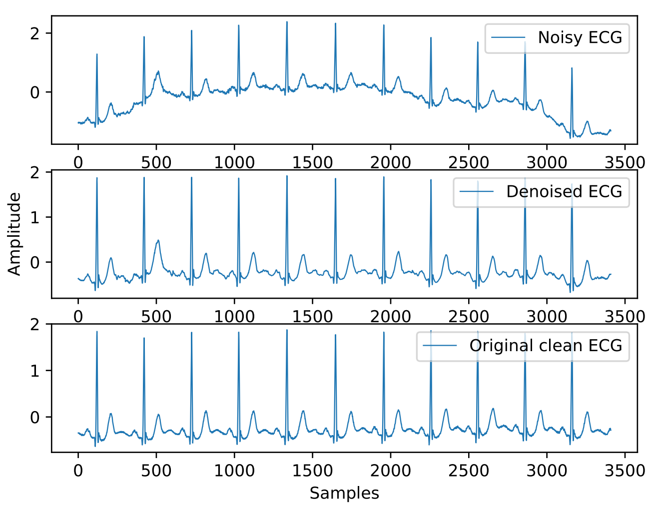
(1) In all cases, the distance function achieves better results than the MSE function.
(2) The additional max function can help learning local characteristics of ECG signals, but it also leads to umsmooth waveforms.
(3) 2 Stages training can overcome the unsmooth problem caused by the additional max function.

5.3. Noise reduction for different noise types

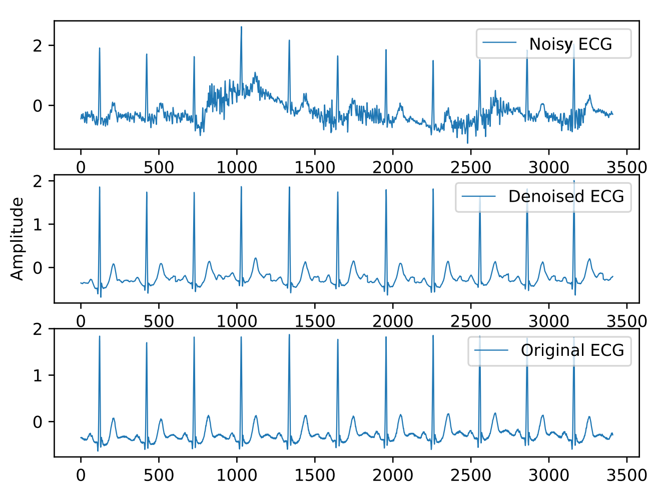
We select ten records numbered 103, 105, 111, 116, 122, 205, 213, 219, 223, 230 in the MIT-BIH Arrhythmia Database, and add



(a) The de-noising results of the ECG signals in removing the EM noise.

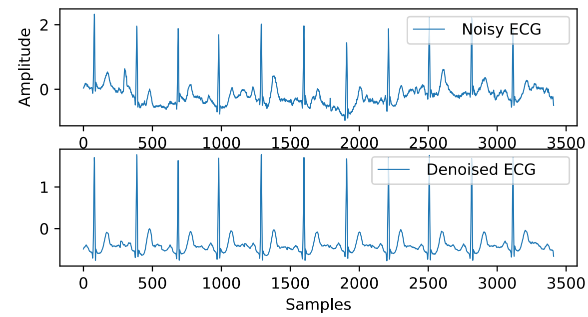


(b) The de-noising results of the ECG signals in removing the BW noise.

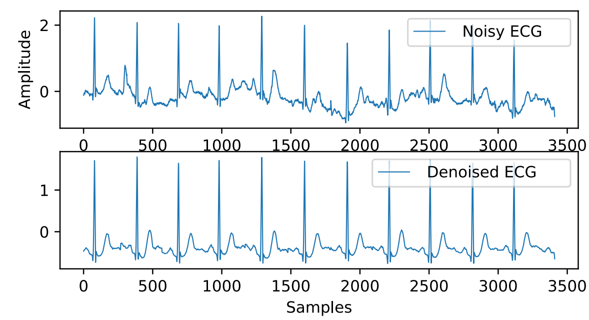


(c) The de-noising results of the ECG signals in removing the MA noise.

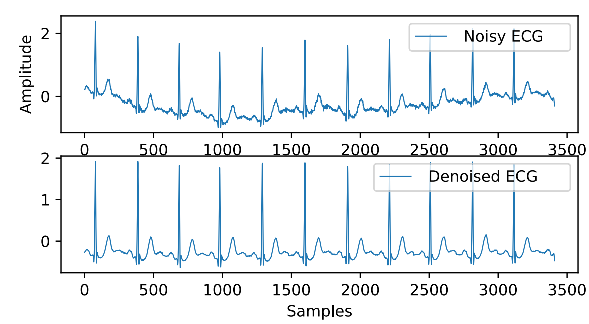
Fig. 7. The experimental results of ECG de-noising in removing the three kinds of noise.



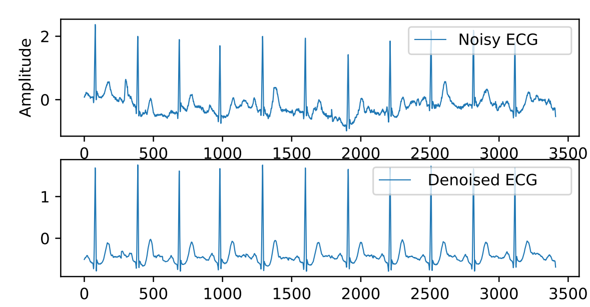
(a) The de-noising results in removing the EM+BW noise.



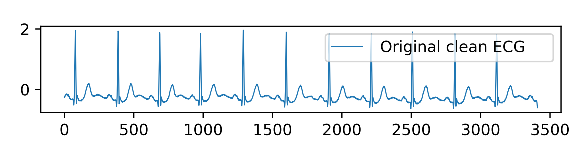
(b) The de-noising results in removing the EM+MA noise.



(c) The de-noising results in removing the BW+MA noise.



(d) The de-noising results in removing the EM+BW+MA noise.



(e) The original clean ECG signals.

Fig. 8. The experimental results of ECG de-noising in removing the mixed noise.

Table 2
The average SNR and RMSE of de-noising results with different kinds of noise.

Original SNR	-	EM	BW	MA	EM+BW	EM+MA	BW+MA	EM+BW+MA
0dB	SNR	32.38	34.83	35.14	30.93	30.24	33.68	30.50
	RMSE	0.0102	0.0062	0.0088	0.0130	0.0138	0.0076	0.0137
1.25dB	SNR	32.9	35.31	35.87	31.33	30.78	34.27	30.95
	RMSE	0.0096	0.0059	0.0081	0.0125	0.0130	0.0071	0.0131
5dB	SNR	33.79	36.29	37.23	32.01	31.70	35.50	31.71
	RMSE	0.0086	0.0053	0.0069	0.0117	0.0118	0.0062	0.0122

the EM, BW and MA noise signals chosen from the MIT-BIH Noise Stress Test Database to each record with the SNR = 0dB, 1.25dB and 5dB respectively. In addition, we take into account the mixed noise cases with multiple noise types, namely EM+BW, EM+MA, BW+MA, and EM+BW+MA. For simplicity, these types of noise are mixed into the original clean signal in an equal proportion. Then, 21 kinds ECG signal records are obtained and are utilized as the experimental data for noise reduction.

Fig. 7 presents the results of ECG de-noising in removing the EM noise, the BW noise as well as the MA noise in our single adversarial model. In subfigures, the upper line represents the noisy ECG signal, the middle line represents the de-noised ECG signals, and the bottom line represents the original clean ECG signals. From the figures, it is observed that the overall de-noised ECG signals are very close to the original ECG signals except for some subtle waveform differences. These results suggest that our method is able to effectively reduce the EM noise, the BW noise as well as the MA noise in ECG signals by a single adversarial model.

Fig. 8 depicts the results of ECG de-noising in removing the mixed noise. In subfigures (a), (b), (c), (d), the upper line represents the mixed noisy ECG signal, namely EM+BW, EM+MA, BW+MA, and EM+BW+MA, and the bottom line represents the de-noised ECG signals. In subfigure (e), the line represents the original clean ECG signals. From these figures, it is also observed that the overall de-noised ECG signals are close to the original ECG signals like Fig. 7. These results suggest that our method is also able to effectively reduce the mixed noise in ECG signals by a single adversarial model.

Table 2 displays the average SNR and RMSE of de-noising results with different kinds of noise. For signals only containing one noise type, our method can achieve up to 37dB on SNR. For signals containing mixed noise, the method can also achieve up to 35dB on SNR.

5.4. Comparison with existing methods

This experiment compares the noise reduction performance of S transform [37], improved WT [16], stacked DAE and improved DAE [24] as well as our proposed method.

Tables 3, 4, 5 show the result SNR and the result RMSE of ten records mentioned in Section 5.3 with different noise types, namely, the MA noise, the EM noise and the BW noise. It is observed that in all cases our proposed method achieves the highest SNR and the lowest RMSE on both individuals and on average. For the MA noise and the BW noise, the average result SNRs are over 34dB; for the EM noise, the average result SNRs are over 32dB.

In Figs. 9, 10, and 11, we assume that the input signals contain the MA noise, the EM noise and the BW noise respectively with SNR = 1.25dB. Figs. 9, 10, and 11 compare the result SNR of de-noised signals. It is observed that in all cases our proposed method achieves the highest SNR. Specifically speaking, the result SNRs of certain records have reached 40dB which implies that the quality of de-noised signals is quite good.

Table 6 presents the SNR improvement over state-of-the-art method (the improved DAE), It is observed that for the MA noise, the EM noise and the BW noise, the average SNRs are improved by 62.57%, 49.45% and 55.34% respectively.

5.5. Quality of signals

One of the most difficult problems of de-noising is how to effectively preserve the abnormal signals of patients while simultaneously removing noise. That is, de-noised ECG signals should have no distortion and still maintain its medical value. In order to analyze whether the noise reduction causes waveform distortion and influences medical judgment, we conduct classification experiments on noisy signals, de-noised signals and original clean signals.

Each record of experimental data described in Section 5.3 has been annotated by two or more cardiologists independently. We classify the experimental data into normal ECG signals and abnormal ECG signals (including atrial premature beat, premature ventricular contraction, pre-excitation, fusion of ventricular and so on) according to annotations. The Support Vector Machine (SVM) algorithm is adopted to classify the normal and the abnormal ECG waveforms.

Table 7 presents the classification accuracy of noisy signals, de-noised signals and original clean signals. It is observed that the accuracy of the de-noised ECG signals with different SNRs experience an increase of 2.94% on average, perhaps reaching up to 7.97%, compared with the noisy ECG signals. More importantly, the accuracy of de-noised signals approaches or even surpasses the accuracy of the original clean ECG signal. For instance, the accuracy of the BW noisy signals with SNR = 0dB is up to 88.02% after de-noising, while the accuracy of the corresponding original clean signals is only 87.67%. These results reflect that our method is able to maintain the medical value of signals effectively.

5.6. Computation performance

In this section, we explore the computation performance of our method. It is important for noise reduction to consider the efficiency in the de-noising process. It is worth noting that the training process of the model is offline. For the online de-noising process, we only utilize the trained generator network model. And the structure of the generator network is 310-250-250-250-310, which only has three hidden layers. Under this structure, the total number of parameters of the generator is approximately 2.8×10^5, which can be loaded within 1MB memory. We performed timing consumption tests on the proposed methods. The test results show that it takes only 6.05×10^{-4} seconds on average to de-noise ECG signals with one cardiac cycle in the de-noising process, which includes data preprocessing and noise reduction. It indicates that our method can fully meet the online processing requirements.

5.7. Discussion

Prior work used decomposition, transform and filtering methods to de-noise ECG signals. However, these studies suffer from several deficiencies: (1) the local and global correlations of ECG

Table 3
Experimental results for removing the MA noise.

MIT-BIH data number			103	105	111	116	122	205	213	219	223	230	Average
S-Transform	0dB	SNR	10.41	10.02	8.21	8.19	9.2	8.32	8.79	10.05	9.95	8.7	9.184
		RMSE	0.302	0.316	0.389	0.389	0.347	0.384	0.363	0.314	0.318	0.367	0.3489
	1.25dB	SNR	10.89	10.42	8.66	8.51	9.67	8.61	9.67	10.61	10.56	9.01	9.661
		RMSE	0.286	0.301	0.369	0.375	0.328	0.371	0.329	0.295	0.297	0.355	0.3306
	5dB	SNR	12.63	12.76	9.94	9.75	11.69	9.91	12.53	12.89	13.44	10.15	11.569
		RMSE	0.234	0.23	0.318	0.325	0.26	0.32	0.236	0.227	0.213	0.311	0.2674
WT method	0dB	SNR	19.66	22.09	20.02	12.44	6.71	21.23	11.83	7.33	18.58	18.03	15.79
		RMSE	0.044	0.040	0.050	0.100	0.182	0.044	0.096	0.149	0.055	0.066	0.083
	1.25dB	SNR	16.87	22.49	19.69	14.40	7.43	20.24	13.27	8.68	20.32	18.86	16.23
		RMSE	0.060	0.039	0.052	0.080	0.167	0.049	0.081	0.127	0.045	0.060	0.076
	5dB	SNR	15.79	24.11	18.81	19.15	11.14	16.51	18.94	14.55	21.41	21.14	18.16
		RMSE	0.067	0.032	0.057	0.046	0.109	0.075	0.042	0.065	0.040	0.046	0.058
Stacked DAE	0dB	SNR	18.92	22.97	22.90	17.92	17.96	20.03	18.18	16.18	20.29	21.11	19.65
		RMSE	0.046	0.036	0.036	0.053	0.047	0.050	0.044	0.049	0.043	0.046	0.045
	1.25dB	SNR	19.07	23.30	22.88	18.48	18.09	20.03	18.70	17.66	21.21	21.22	20.06
		RMSE	0.045	0.035	0.036	0.049	0.042	0.050	0.041	0.044	0.039	0.045	0.043
	5dB	SNR	19.31	24.12	22.95	20.61	21.73	20.14	20.15	20.05	23.69	21.33	21.41
		RMSE	0.044	0.032	0.035	0.038	0.031	0.050	0.036	0.033	0.029	0.044	0.037
Improved DAE	0dB	SNR	21.38	24.72	23.15	19.22	19.57	24.23	19.59	18.80	22.91	22.58	21.62
		RMSE	0.034	0.030	0.035	0.045	0.040	0.031	0.038	0.039	0.032	0.038	0.036
	1.25dB	SNR	22.41	24.86	23.27	20.22	20.02	24.49	19.78	19.63	23.41	22.60	22.07
		RMSE	0.031	0.029	0.034	0.040	0.038	0.030	0.037	0.034	0.030	0.038	0.034
	5dB	SNR	23.33	25.13	23.33	22.41	20.63	24.67	20.63	21.97	24.21	22.63	22.89
		RMSE	0.027	0.028	0.034	0.031	0.036	0.030	0.034	0.027	0.028	0.038	0.031
Proposed method	0dB	SNR	**41.36**	**36.49**	**35.9**	**32.47**	**31.06**	**40.58**	**33.73**	**32.37**	**33.46**	**33.98**	**35.14**
		RMSE	**0.0042**	**0.0073**	**0.0079**	**0.0107**	**0.0126**	**0.0045**	**0.01**	**0.0112**	**0.01**	**0.0098**	**0.0088**
	1.25dB	SNR	**42.1**	**37.46**	**36.16**	**33.67**	**31.88**	**41.19**	**34.26**	**33.4**	**34.36**	**34.22**	**35.87**
		RMSE	**0.0038**	**0.0065**	**0.0076**	**0.0093**	**0.0115**	**0.0042**	**0.0094**	**0.01**	**0.009**	**0.0096**	**0.0081**
	5dB	SNR	**43.24**	**39.55**	**36.66**	**35.88**	**33.5**	**42.22**	**34.95**	**35.38**	**36.35**	**34.55**	**37.23**
		RMSE	**0.0033**	**0.005**	**0.0072**	**0.0072**	**0.0096**	**0.0037**	**0.0087**	**0.008**	**0.0072**	**0.0092**	**0.0069**

Table 4
Experimental results for removing the EM noise.

MIT-BIH data number			103	105	111	116	122	205	213	219	223	230	Average
S-Transform	0dB	SNR	6.41	6.13	5.45	5.47	5.87	5.59	5.85	6.05	6.21	6.29	5.932
		RMSE	0.478	0.493	0.534	0.533	0.509	0.525	0.51	0.498	0.489	0.484	0.5053
	1.25dB	SNR	7.47	7.35	6.4	6.32	6.96	6.47	7.06	7.17	7.45	7.48	7.013
		RMSE	0.423	0.429	0.478	0.483	0.449	0.475	0.444	0.438	0.424	0.423	0.4466
	5dB	SNR	10.32	10.4	8.54	8.32	9.60	8.55	10.12	10.04	10.74	10.45	9.708
		RMSE	0.305	0.302	0.374	0.384	0.331	0.374	0.312	0.315	0.290	0.300	0.3287
WT method	0dB	SNR	9.51	21.47	9.34	9.63	9.71	18.29	15.02	13.15	18.11	11.99	13.62
		RMSE	0.138	0.044	0.171	0.138	0.128	0.063	0.067	0.076	0.058	0.132	0.102
	1.25dB	SNR	10.37	23.08	9.65	10.56	9.51	20.30	15.80	13.85	21.10	12.93	14.72
		RMSE	0.125	0.037	0.165	0.124	0.132	0.050	0.061	0.070	0.040	0.119	0.092
	5dB	SNR	13.07	28.37	14.96	13.77	8.65	21.36	19.20	16.20	24.05	15.91	17.55
		RMSE	0.091	0.020	0.090	0.086	0.145	0.043	0.040	0.054	0.029	0.084	0.068
Stacked DAE	0dB	SNR	18.94	23.45	22.33	19.18	17.87	20.08	19.20	17.53	22.66	20.79	20.20
		RMSE	0.047	0.035	0.038	0.046	0.047	0.050	0.039	0.045	0.033	0.048	0.043
	1.25dB	SNR	19.07	23.82	22.43	19.69	18.98	20.11	19.74	18.32	23.20	20.91	20.63
		RMSE	0.046	0.033	0.038	0.043	0.042	0.049	0.037	0.041	0.031	0.047	0.041
	5dB	SNR	19.30	24.56	22.66	21.00	21.16	20.24	20.98	20.08	24.39	21.40	21.58
		RMSE	0.041	0.030	0.037	0.037	0.033	0.049	0.033	0.034	0.027	0.044	0.037
Improved DAE	0dB	SNR	22.75	23.70	23.39	21.34	17.70	23.47	19.33	18.38	23.17	22.40	21.56
		RMSE	0.029	0.033	0.034	0.035	0.050	0.033	0.040	0.041	0.031	0.039	0.037
	1.25dB	SNR	22.97	23.94	23.57	21.82	18.76	23.57	19.79	19.07	23.55	22.54	21.96
		RMSE	0.029	0.033	0.033	0.033	0.042	0.033	0.037	0.038	0.030	0.038	0.035
	5dB	SNR	23.45	24.66	23.65	23.08	20.81	23.66	20.69	21.01	24.00	22.81	22.78
		RMSE	0.027	0.030	0.033	0.030	0.035	0.030	0.034	0.030	0.028	0.037	0.031
Proposed method	0dB	SNR	**38.09**	**34.27**	**33.07**	**30.02**	**28.74**	**38.44**	**30.27**	**28.24**	**31.75**	**30.87**	**32.38**
		RMSE	**0.005**	**0.008**	**0.0093**	**0.0115**	**0.0134**	**0.0048**	**0.0125**	**0.015**	**0.0101**	**0.0119**	**0.0102**
	1.25dB	SNR	**38.56**	**34.79**	**33.45**	**30.77**	**29.28**	**38.96**	**30.68**	**29.21**	**32.19**	**31.11**	**32.9**
		RMSE	**0.0049**	**0.0075**	**0.0089**	**0.0105**	**0.0126**	**0.0046**	**0.0119**	**0.0134**	**0.0096**	**0.0116**	**0.0096**
	5dB	SNR	**39.39**	**35.67**	**34.1**	**31.72**	**30.01**	**39.89**	**31.37**	**31.23**	**32.96**	**31.53**	**33.79**
		RMSE	**0.0044**	**0.0068**	**0.0082**	**0.0095**	**0.0116**	**0.0041**	**0.011**	**0.0106**	**0.0088**	**0.0111**	**0.0086**

Table 5
Experimental results for removing the BW noise.

MIT-BIH data number			103	105	111	116	122	205	213	219	223	230	Average
S-Transform	0dB	SNR	11.4	11.56	9.22	9.01	10.58	9.31	11.57	11.55	12.14	11.68	10.802
		RMSE	0.269	0.264	0.346	0.354	0.296	0.342	0.264	0.265	0.247	0.261	0.2908
	1.25dB	SNR	12.06	12.23	9.61	9.35	11.17	9.7	12.22	12.22	12.95	12.35	11.386
		RMSE	0.249	0.245	0.331	0.341	0.276	0.327	0.245	0.245	0.225	0.241	0.2725
	5dB	SNR	13.54	13.77	10.41	10.04	12.38	10.46	13.77	13.65	14.81	13.89	12.672
		RMSE	0.21	0.205	0.302	0.315	0.24	0.3	0.205	0.208	0.182	0.202	0.2369
WT method	0dB	SNR	14.87	31.53	18.41	20.00	9.12	22.64	20.83	18.69	17.34	22.23	19.57
		RMSE	0.074	0.014	0.060	0.042	0.138	0.037	0.034	0.040	0.063	0.041	0.054
	1.25dB	SNR	14.88	31.91	18.42	20.06	8.54	22.73	20.47	20.22	17.40	22.22	19.69
		RMSE	0.074	0.013	0.060	0.042	0.147	0.037	0.036	0.034	0.063	0.041	0.055
	5dB	SNR	14.90	32.71	18.43	20.10	8.22	22.91	19.11	21.44	17.51	22.18	19.75
		RMSE	0.074	0.012	0.060	0.041	0.153	0.036	0.042	0.029	0.062	0.041	0.055
Stacked DAE	0dB	SNR	20.38	24.90	23.04	18.84	19.48	20.08	19.92	19.30	22.94	20.53	20.94
		RMSE	0.038	0.029	0.035	0.047	0.040	0.050	0.036	0.037	0.031	0.049	0.039
	1.25dB	SNR	20.55	23.27	23.07	19.53	19.90	20.12	20.32	19.83	23.74	20.67	21.30
		RMSE	0.038	0.028	0.035	0.043	0.038	0.049	0.035	0.035	0.029	0.048	0.038
	5dB	SNR	20.77	25.47	23.03	21.60	21.00	20.30	21.34	21.15	25.41	21.03	22.11
		RMSE	0.037	0.027	0.035	0.034	0.034	0.048	0.031	0.030	0.024	0.046	0.035
Improved DAE	0dB	SNR	23.78	25.40	23.31	23.51	20.07	20.07	21.30	23.02	24.25	22.72	22.74
		RMSE	0.026	0.028	0.034	0.027	0.050	0.050	0.032	0.024	0.027	0.037	0.034
	1.25dB	SNR	23.82	25.42	23.32	23.59	20.08	20.08	21.36	23.31	24.41	22.74	22.81
		RMSE	0.026	0.028	0.034	0.027	0.050	0.050	0.032	0.023	0.027	0.037	0.033
	5dB	SNR	23.89	25.45	23.35	23.76	20.08	20.08	21.46	24.08	24.64	22.79	22.96
		RMSE	0.025	0.027	0.034	0.026	0.050	0.050	0.031	0.021	0.026	0.037	0.033
Proposed method	0dB	SNR	**40.26**	**39.49**	**34.13**	**32.81**	**32.09**	**39.7**	**31.64**	**31.23**	**34.59**	**32.36**	**34.83**
		RMSE	**0.0032**	**0.0035**	**0.0066**	**0.0068**	**0.0075**	**0.0034**	**0.0086**	**0.0086**	**0.0059**	**0.0081**	**0.0062**
	1.25dB	SNR	**40.72**	**39.87**	**34.53**	**33.51**	**32.42**	**40.34**	**32.05**	**32.09**	**35.12**	**32.44**	**35.31**
		RMSE	**0.0031**	**0.0034**	**0.0063**	**0.0063**	**0.0072**	**0.0031**	**0.0082**	**0.0078**	**0.0056**	**0.008**	**0.0059**
	5dB	SNR	**41.6**	**40.56**	**35.27**	**34.99**	**32.89**	**41.73**	**32.89**	**34.05**	**36.33**	**32.58**	**36.29**
		RMSE	**0.0027**	**0.0031**	**0.0058**	**0.0053**	**0.0068**	**0.0027**	**0.0074**	**0.0062**	**0.0048**	**0.0079**	**0.0053**

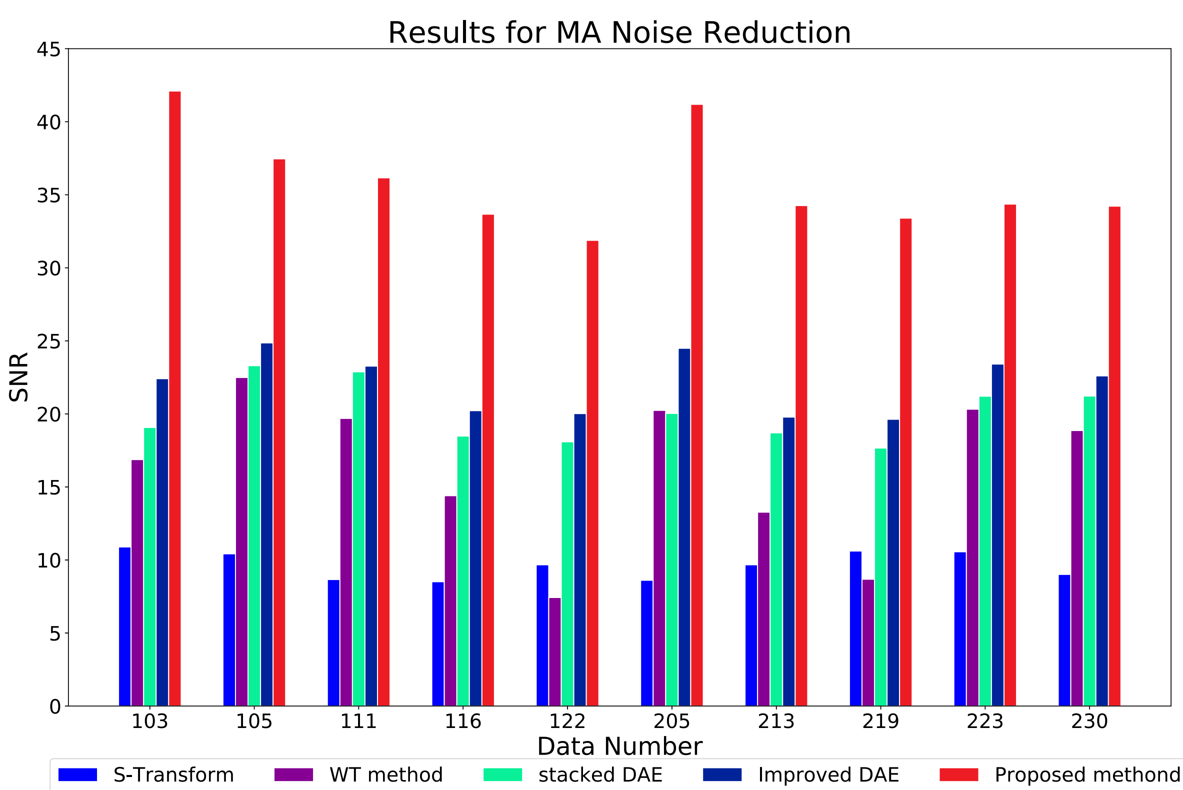


Fig. 9. A comparison of SNR with different methods for MA noise with SNR = 1.25dB.

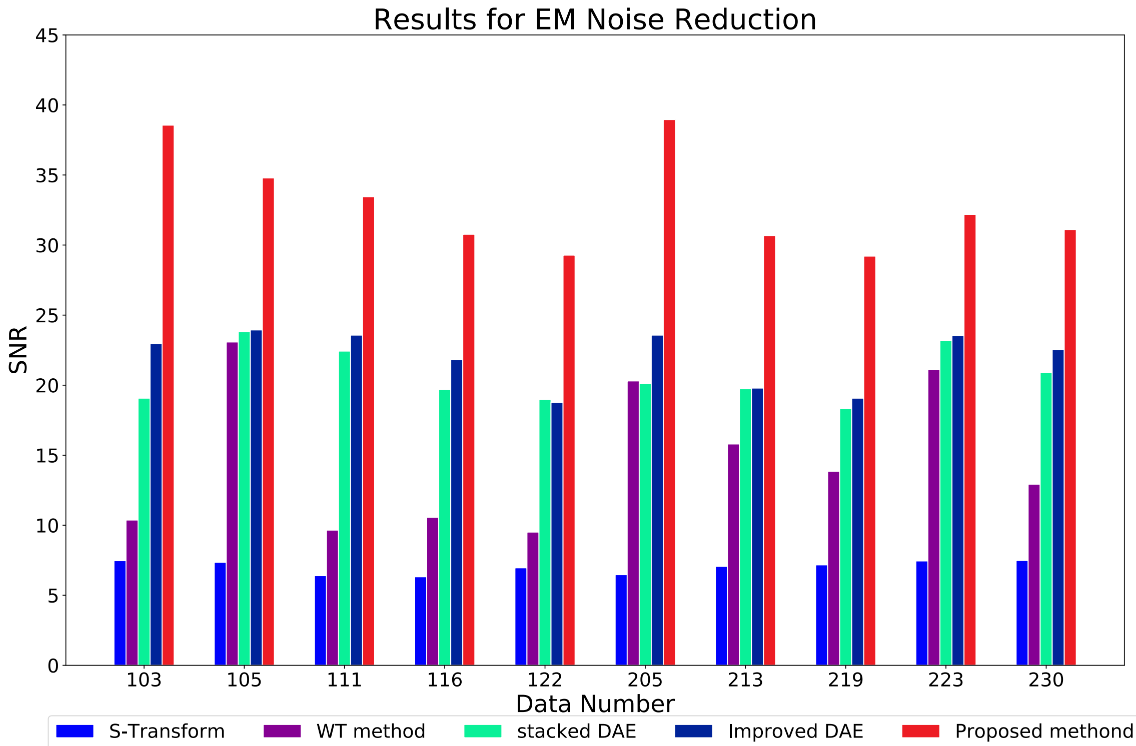


Fig. 10. A comparison of SNR with different methods for EM noise with SNR = 1.25dB.

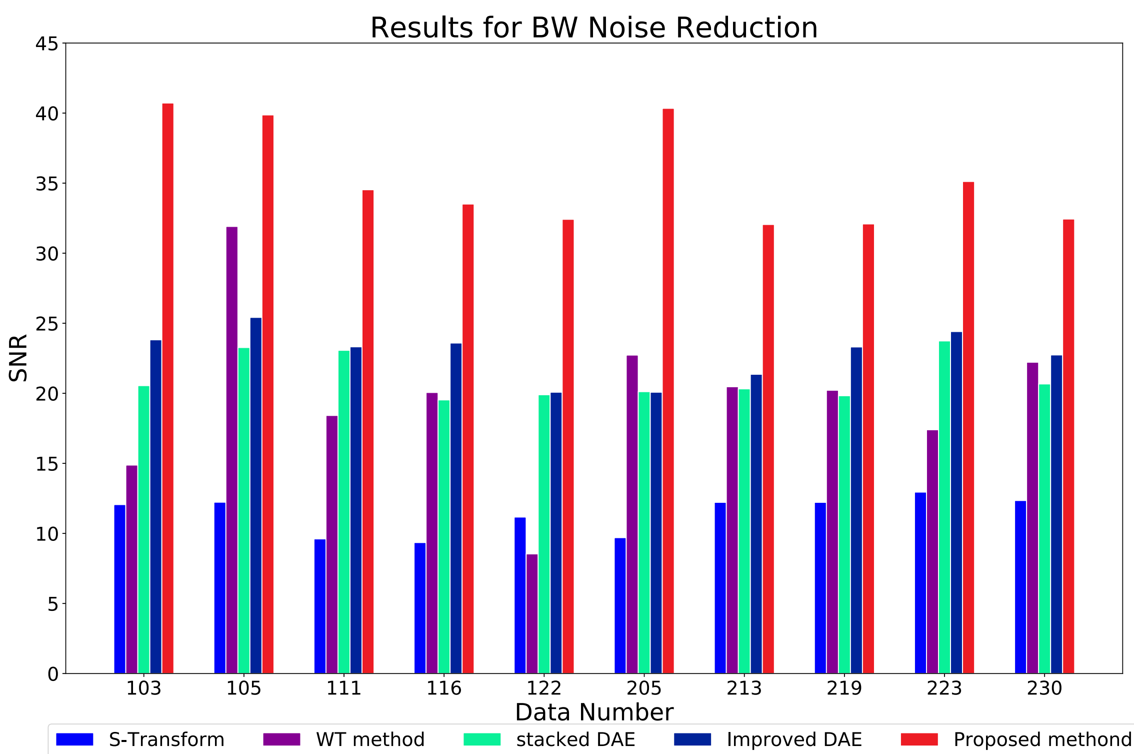


Fig. 11. A comparison of SNR with different methods for BW noise with SNR = 1.25dB.

signals are not considered comprehensively; (2) adaptability is not good enough for various noise; (3) severe distortion in signals may be triggered.

In this study, we establish a new view on the adversarial method, i.e., the adversarial method has the ability to learn the difference between the input and the output. The view makes possible de-noising ECG signals with the adversarial method. To the best of our knowledge, this is the first paper explaining why adversarial method can be used for noise reduction. we believe that the view can effectively promote the further applications of the adversarial method.

We propose a new loss function $L_G(\Theta) = l_{real} + \lambda l_{dist} + \beta l_{max}$. l_{max} makes the model concentrate on the local maximum difference between the de-noised signals and the original clean signals;

Table 6
The percent of SNR improvement over the state-of-the-art method (improved DAE).

SNR/Noise type	MA noise	EM noise	BW noise
0dB	62.53%	50.19%	53.17%
1.25dB	62.53%	49.82%	54.8%
5dB	62.65%	48.33%	58.06%
Average	62.57%	49.45%	55.34%

Table 7
A comparison of the waveform classification accuracy.

SNR	Noise type	Original ECG	Denoised ECG	Noisy ECG	Improve-ment
0dB	EM	87.76%	85.02%	79.14%	**5.88%**
	MA	84.69%	83.41%	83.06%	**0.35%**
	BW	87.67%	88.02%	85.96%	**2.06%**
1.25dB	EM	87.06%	86.03%	78.06%	**7.97%**
	MA	86.55%	84.43%	83.54%	**0.89%**
	BW	84.56%	87.86%	84.59%	**3.27%**
5dB	EM	84.45%	85.31%	81.34%	**3.97%**
	MA	86.65%	84.05%	83.03%	**1.02%**
	BW	84.96%	88.61%	87.57%	**1.04%**
Average	–	86.04%	85.86%	82.92%	**2.94%**

while l_{dist} makes the model focus on the global difference between the de-noised signals and the original clean signals. With the help of 2 stages training, the new loss function achieves the best noise reduction performance. The loss function design method takes full account of both global and local characteristics of signals, and extend the design method of loss function of a wide range of machine learning problems.

We propose an adversarial de-noising method of ECG signals. we found that our method is able to effectively reduce various types of noise in ECG signals by a single adversarial model. These results verify that the the adversarial method has more power on generalization capability than other deep learning method.

We evaluate the de-noised ECG signals qualitatively by Support Vector Machine (SVM) algorithm. we found that the accuracy of de-noised signals by our de-noising method approaches or even surpasses the accuracy of the original clean ECG signal. These findings imply that the adversarial de-noising method not only preserves the medical characteristics of signals, but enhances these characteristics to some extent in some cases.

6. Conclusion

We have investigated adversarial de-noising method of ECG signals, i.e., obtaining a high quality useful signals from the noisy ECG signals using adversarial method. Our investigation is based on the adversarial method, which accumulate knowledge on the data continuously through the game between the generator and the discriminator. First, we have established a new view on the adversarial method to explain why it can be used for noise reduction. Second, we have proposed a new loss function that acts as a more effective alternative for getting high quality signals. Third, we have proposed an adversarial de-noising method of ECG signals, which make full use of the generalization capability of the adversarial method. Last, we have evaluated the quality of signals by the SVM algorithm.

However, some limitations are worth noting. (1) The analytical theory of difference learning of the adversarial method is not established. (2) The length of the training samples is limited within a heartbeat period. Future research efforts should be directed towards this direction.

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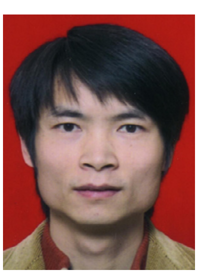

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