DEEP GENERATIVE MODELS FOR ECG DENOISING AND FILTERING

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ABSTRACT

The Electrocardiography(ECG) heartbeat classification is essential for early recognition of cardiac arrhythmia. As a record of the electricity signal of myocardium, ECG usually suffers from different noises in the real world and usually result in misdiagnoses by human or machine learning-based methods. In this work, we propose two deep generative models to reconstruct ECG signals from corrupted ones. Then we can use existing methods to acquire the timestamps of R-peaks in the ECG signal, which lead to proper segmentation of heartbeats for better classification afterward. All of our source code can be found at [1]

1 Introduction

Deep learning had demonstrated a state of art performance in detecting arrhythmia the past decade and several deep learning based methods were proposed for ECG denoising, including Recurrent Neural Networks (1) and Convolution Neural Networks (3). Unsupervised feature extraction and filtering approaches based on autoencoder were also proposed. (11) (10). However, in order to perform heartbeat-wise classification task, we need to segment out each heartbeat from raw ECG signals. Traditionally, we apply some filters on the raw ECG signal to make it more suitable for R-peaks finding algorithms. When doing ECG classification to detect irregular rhythms, traditional noise filtering methods such as finite impulse response filter(FIR) (9) were usually applied on the raw signal which helps to segment the heartbeat for further analysis correctly. However, when the signal contains lots of noises, the performance of such filters decreases drastically. Consequently, the segmentation could not be performed properly which leads to the poor performance of the classifier. In this work, we aim to develop and validate deep generative models, including Denoising AutoEncoder (DAE) and Denoising Generative Adversarial Networks (DGAN) on ECG denoising to benefit heartbeat segmentation and classification afterward.

2 Related Work

2.1 Finite Impulse Response Filter

FIR filter (9) is a common tool used in signal processing. It is a filter whose impulse response is of finite duration, because it settles to zero in finite time. FIR filter performs convolution on the input signal with a predefined impulse sequence. A moving average filter is a simple FIR filter with the impulse sequence being one over the window size. In order to give a baseline on how well we can correctly locate R-peaks given a noise ECG raw signal, we will evaluate our proposed models in comparison to FIR filter later in the experiments.

[1] `https://github.com/ernestchu/noise-ecg-classification/`

2.2 AutoEncoder

Autoencoder (2) is composed of two parts of neural networks called encoder and decoder respectively. While the encoder tries to compress the important feature of a given data into a low dimentional latent vector, the decoder reconstructs data from the latent vector. Enforcing a L2 Loss on the generated output and the paired data from other domains, we can get the semantic information and transform the original data to the corresponding domain.

2.3 Pixel-to-Pixel Generative Adversarial Networks

Pixel-to-pixel GAN (7) was proposed for the image translation task. It is a variation of conditional GAN on images (8). In addition to a L1 loss wich is similar to the one used in autoencoder, an adversarial loss (5) was also considered. With the help of the discriminate neural network, we can generate clearer images. We adapt this concept to the domain of signals, using it in our DGAN which reconstructs clean signals from the noisy one.

3 Methodology

3.1 Denoising Procedures

Upon given a raw ECG signal, we first divide it into fixed-sized segments in order to be fed into neural networks. We proposed two generative models DAE, DGAN to denoise noisy data. They are based on autoencoder and generative adversarial networks respectively. Next we combine these generated signal segments back in to a full-time ECG signal. With this processed signal, we can perform QRS detection (6) and get the location of R-peaks, futher obtaining 0.7-second heartbeat segments for each R peak. Serving the purpose of both theoratical and pratical uses, we then use a classifier pretrained on clean ECG signal to give each R peak an arrhythmia label. Finally we evaluate different models on the label correctness and R peak location.

3.2 Denoising AutoEncoder

In this work we propose an approach based on DAE for signal denoising, as well as for compressing the size of ECG waveforms. The proposed DAE consists of an encoder and a decoder with 8 layers respectively, as in Figure 1. In the encoder, the size of ECG signals is reduced, and the signals are encoded into low dimensional features. The decoder tries to reconstruct an output depending on the low dimensional features. We employed tanh as activation functions for hidden layers.

The encoder contains a series of layers, where each individual layer is composed of a one dimensional convolution layer and an activation layer. In the encoder of the model, the original signals with size of 1×3600 are taken as input, and a convolutional process with 64 filters of size 4×1, stride of 2 and padding of 1 is applied on the first layer. The following convolutional layers double the channels until 512 with kernel size, stride and padding remain the same as the first layer. Through the encoding process, a 1×1 dimensional feature map is obtained. This feature map also represents the compressed data. The decoder part is inversely symmetric to the encoder. Here, the deconvolutional layers proceed to up-sample the feature maps, and to recover structural details. As for the output layer, a deconvolutional layer with 1 filter of size 4×1 generate the output signal. We also established skip connections between encoder and decoder layers at the corresponding levels in the U-net (12) fashion, enabling the fusion of informations in different depth. Finally, we compute the MSE loss between the generated signal and the clean signal and backpropagate.

3.3 Denoising Generative Adversarial Networks

Very similar to DAE, DGAN 2 uses the same autoencoder as its generator. However, instead the MSE loss, here we use L1 loss as Isola et al.(7) indicate. Furthermore, an adversarial loss was imposed with an additional discriminator. The discriminator takes the generated signal concatenated with the original raw signal as input, serving as the condition. Also, the concatenated clean signal is also fed into the discriminator whose task is to tell wether the input signal is clean, as the adversarial property in GAN (5).

3.4 Heartbeat Segmentation and Annotation

When we get a raw ECG signal, we would first try to get rid of noises that could affect the performance of heartbeat segmentation and classification. We would perform desired method to reconstruct a clean ECG signal, which is the target task we will focus on in this work. Then, with the processed signal, we use Hamiton segmenter (6) to find R-peaks, which lead to reasonable heartbeat segmentation. Finally, we use a pretrained deep neural network to classify these segments, generating a list of labels along with the corresponding timestamps on the signal samples which are

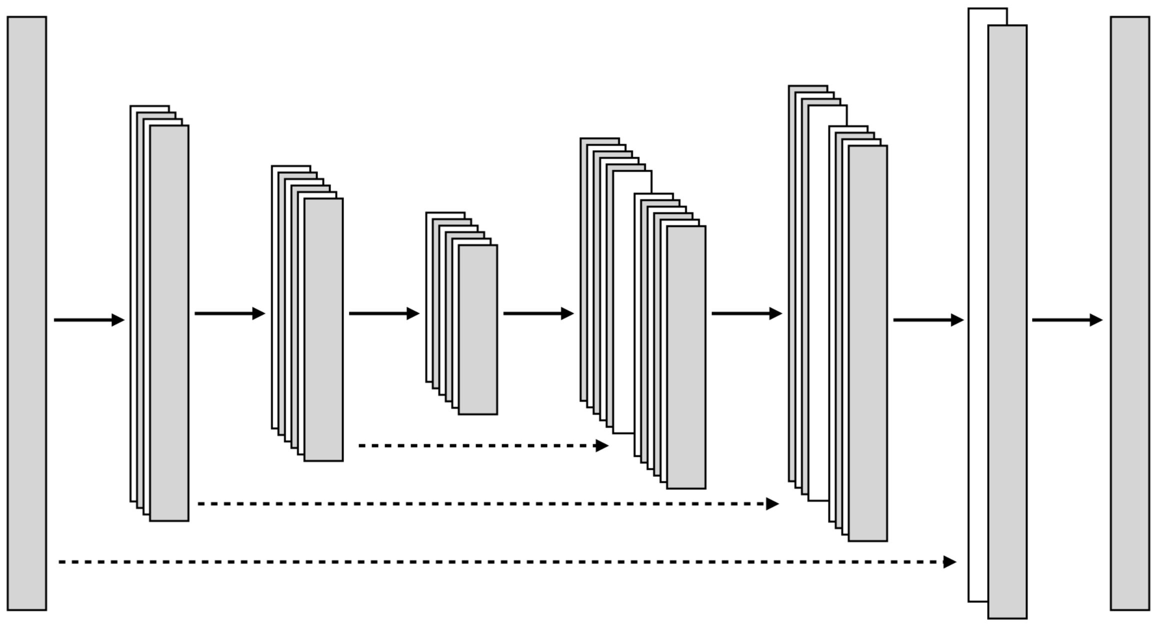

Figure 1: Denoising AutoEncoder

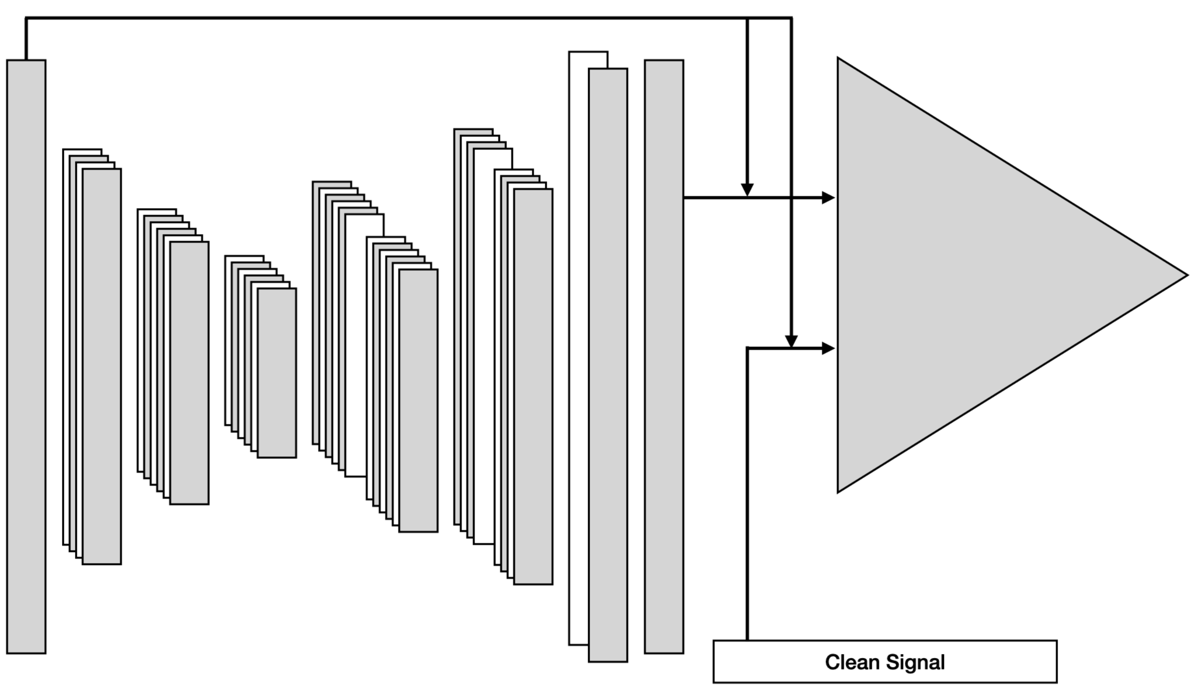

Figure 2: Denoising Generative Adversarial Networks

actually R-peaks locations earlier. We compare the predicted information with the ground truth as a way to evaluate the models.

4 Experiment

4.1 Experimental Data

We collected noised signals from MIT-BIH Noise Stress Test Database (MBNSTD) (4). This database includes half-hour ECG recordings in ambulatory ECG recordings. The three noise records were assembled from the recordings by selecting intervals that contained predominantly baseline wander, muscle (EMG) artifact, and electrode motion artifact. Electrode motion artifact is generally considered the most troublesome, since it can mimic the appearance of ectopic beats and cannot be removed easily by simple filters, as can noise of other types.

The ECG noises were created using two clean recordings, identification number 118 and 119 from the MIT-BIH Arrhythmia Database (4), to which calibrated amounts of noise of electrode motion artifact. 2 minutes Noise and Clean signals in alteration were added after the first 5 minutes of each record. There were six different Signal-to-Noise (SNR) ratio levels from best to worst quality (24db, 18db, 12db, 6db, 0db, -6db) generated into six different 30-mins ECG recordings. We also collected clean ECG recordings of 118 and 119 to be the ground true data.

All collected ECG recordings first went through time specific fragmentation to gather a group 10-second ECG data of 360 Hz sampling rate. We then randomly split all ECG data into training set and test set in 7:3 ratio.

4.2 Annotating Process

When we get a raw ECG signal, we would first try to get rid of noises that could affect the performance of heartbeat segmentation and classification. We would perform desired method to reconstruct a clean ECG signal, which is the target task we will focus on in this work. Then, with the processed signal, we use Hamiton segmenter (6) to find R-peaks, which lead to reasonable heartbeat segmentation. Finally, we use a trained deep neural networks to classify these segments, generating an list of labels along with the corresponding timestamps on the signal samples which are acutally R-peaks locations earlier. We compare the predicted informations with the ground truth as a way to evaluate the models.

4.3 Evaluate Different Models

We first train a deep neural networks on the half-hour ECG signals from MIT-BIH Arrhythmia Database (4) and achieve 0.95 accuracy on both training data and evaluating data. We segment the signals into 252-d vectors based on the R-peaks timestamps in the ground truth. The number 252 is derived from the average heart rate of 85bpm and the sample rate of 360Hz. Detailed training process and source code can be found on our github. The denoising method we use in baseline model is FIR filtering (9). We use one of the dataset from MIT-BIH Noise Stress Test Database (MBNSTD) (4) including six levels of noise in the patient's ECG. The two proposed models are also trained under such configurations. We shall see the result in next section. The performance used for evaluating the model is truth positive divide by number N of R-peaks in the ground truth.

$$Performance = \frac{TP}{N}$$

Where truth positive is the number of predicted instances whose label are correct and the R-peak is matched under a small tolerance.

4.4 Result

Result and the source code are at Table 1 and our github [2] respectively.

5 Discussion

This study demonstrated the result of 2 different deep learning methods on denoising ECG signals and later on heartbeat segmentation and classification. Previous studies regarding deep learning based denoising methods had focused on

[2] https://github.com/ernestchu/noise-ecg-classification/tree/main/src/experiments

Table 1: Result (Performance)

SNR	-6	0	6	12	18	24
Models						
FIR	0.44	0.57	0.67	**0.84**	**0.93**	**0.94**
DAE (ours)	**0.63**	**0.67**	**0.68**	0.69	0.68	0.69
DGAN (ours)	0.61	0.66	**0.68**	0.68	0.68	0.68

single noise level and mostly were performed after heartbeat segmentation (10). In this study, we obtained ECG from MBNSTD, which included 6 different noise levels that were more similar to clinical situations. And compared to previous studies, we performed denoising techniques prior to heartbeat segmentation. The result showed that deep learning methods were able to achieve better performance on reconstructing EGG signals from severe corrupted ones. In ECG with minor noise, FIR filter had outperformed both DAE and DGAN method on denoising ability. This result may be due to weight sharing and interaction during model training among different noise levels. There might be various approaches to further improve the model performance. One of them is to develop a noise level classifier before applying denoising models. The denoising models then trained through different levels to avoid weight sharing. Another way is to obtain more data from the same database, either by separating ECG samples in shortened duration or using different ECG lead recordings. Singh et al had tried to generate noise signals by themselves from the MIT arrythmia database that enrolled 10 different individuals, and showed better a result on GAN-based denoising method (13).

6 Limitation

Our proposed deep learning based denoising methods both required ground truth samples of good quality for signals reconstruction, which was usually not practical in real world tasks. Nevertheless, if we're able to develop these models based on ECG records from a bigger population, wide range data variability may lower the barrier for interpersonal application.

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