Image Denoising by AutoEncoder: Learning Core Representations

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Abstract. In this paper, we implement an image denoising method which can be generally used in all kinds of noisy images. We achieve denoising process by adding Gaussian noise to raw images and then feed them into AutoEncoder to learn its core representations(raw images itself or high-level representations).We use pre-trained classifier to test the quality of the representations with the classification accuracy. Our result shows that in task-specific classification neuron networks, the performance of the network with noisy input images is far below the preprocessing images that using denoising AutoEncoder. In the meanwhile, our experiments also show that the preprocessed images can achieve compatible result with the noiseless input images.

Keywords: Image Denoising, Image Representations, Neuron Networks, Deep Learning, AutoEncoder.

1 Introduction

1.1 Image Denoising

Image is the object that stores and reflects visual perception. Images are also important information carriers today. Acquisition channel and artificial editing are the two main ways that corrupt observed images. The goal of image restoration techniques [1] is to restore the original image from a noisy observation of it. Image denoising is common image restoration problems that are useful by to many industrial and scientific applications. Image denoising problems arise when an image is corrupted by additive white Gaussian noise which is common result of many acquisition channels. The white Gaussian noise can be harmful to many image applications. Hence, it is of great importance to remove Gaussian noise from images. This paper focuses on image denoising.

Some approaches have been focus on the denoising process. The common ideas of theses approaches is to transfer image signals to an alternative domain where they can be more easily separated from the noise [2, 3]. With the development of deep artificial neuron networks, end-to-end denoising process can be achieved. In this paper, we use AutoEncoder [4] to achieve image denoising.

1.2 Approach and Dataset

With the prosper development of neural networks, image denoising by neural networks [5] has been a hot topic. We implement an AutoEncoder that can efficiently remove Gaussian noise from images.

Handwritten digit images are commonly used in optical character recognition and machine learning research [6]. Due to its property of binary images, these Handwritten digit images are easily influence by white Gaussian noise. In order to see whether our algorithm extract the core information of an image, we use the MNIST dataset [7], which contains 60000 training images and 10000 testing images of handwritten digits from 250 persons to test ability of our algorithm.

1.3 Versatility

Image denoising is a kind of feature representation extraction process. A good denoising algorithm should not just work well on removing all kinds of noises, but also should work effectively. Deep neuron networks is powerful in some image classification task nowadays, however, some noise of input images can change its performance. Some research such as 'One pixel attack for fooling deep neural networks'[8] from another aspect states the importance of image denoising. In order to emphasize the performance of input images' quality, we also feed raw images, noisy images and denoised images to certain classification neuron networks. The performance of the denoised images that generated by our proposed algorithm on some classification network will reveal on how well this algorithm works on image denoising.

In a nutshell, we are trying to use AutoEncoder to achieve image denoising and test the quality of denoised images by feeding them into pre-trained neuron networks to see its accuracy compared with noisy or noiseless images.

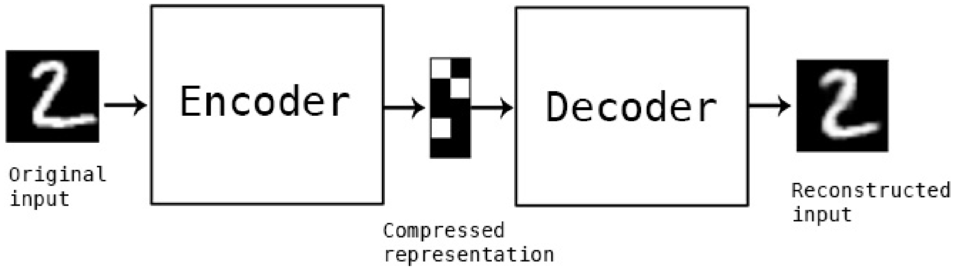

Fig. 1. How AutoEncoder network works [11]

2 Method

2.1 AutoEncoder Networks

Some researcher pointed out that AutoEncoder have the ability to learn core representations of digit signals and you can do what you want with the network structure only if restrict your expected output to be the same or similar to the input [9]. Besides, [10] pointed out that AutoEncoder can be effectively in image recovery. Hence, we decide to use AutoEncoder removing noise from images.

Autoencoding is a data compression algorithm that have both the compression and decompression functions. AutoEncoder has there main properties that are data-specific, lossy and can learn core representations automatically from input examples without any supervision signals. Hence, it belongs to unsupervised learning [12]. Moreover, in the content of AutoEncoder nowadays, both the encoder and decoder are generally neuron networks. To be specific, Autoencoder is data-specific for the network can only be used to compress data similar to what they have been trained on, so this structure is task-specific. Autoencoder is also lossy, which means that the the output can have poor performance sometimes. Autoencoder is learned automatically from data examples and it is a end-to-end training process.

In our case, we use deep neuron networks as the encoding function and the decoding function. Mean squared error loss function is being chosen for the distance function between the input and the output. To be specific, we use convolution neuron networks (CNN) [13], ReLU activation [14] and Maxpooling of Pytorch [15] in encoder network. We use deconvolution neuron networks (a special CNN structure), ReLu activation and and Maxpooling of Pytorch in decoder network. Besides, batch normalization [16] are used in both encoder and decoder network.

As AutoEncoder network can achieve image compression from its the hidden neurons' output, because the hidden layer can learn a compressed feature representation for the input data. We also can achieve decompression by the output layer because the output value size is the same of the input.

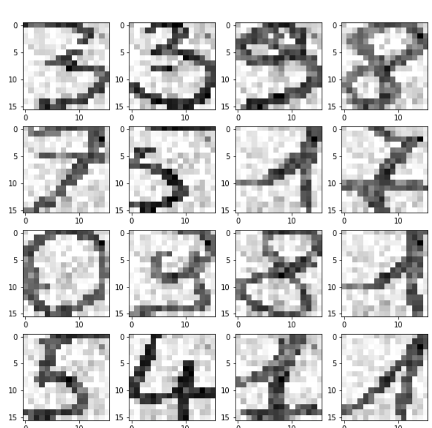

Fig. 2. Compressed images have generated noise

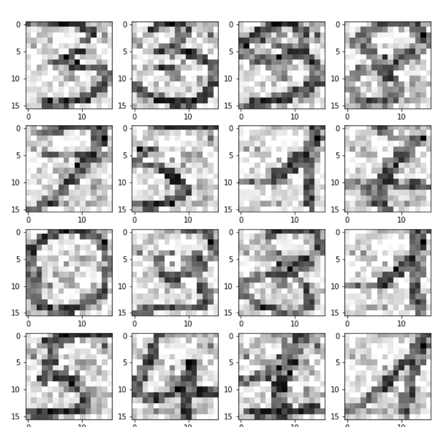

Fig. 3. More noise with higher compression rate

2.2 Denoising method and relevant thinking

In our previous work, we have done image compression with pruning by using [17]. According to the result (Fig2 and Fig3), we can see that the output images after pruning have something like Gaussian noise. If the denoising method works, we can use it to modify the compression images by removing some noise information.

We are aiming to get noiseless images. To achieve that, we first add white Gaussian noise to original images. We treat these noise-added images as the input of AutoEncoder and the desired output from decoder are the original images (images that have no added white Gaussian noise). We use this denoising method because we think that the added white noise are not parts of the core representations of the input images. So those added noise will be filtered by the encoder and the compressed representations have no noise information, thus the output of decoder should be clean and noiseless images.

2.3 Training Strategies

As we want to use the output from the AutoEncoder to form an images, the network should produce positive output. Hence, we adding ReLU activation at the last the output layer of decoder, which can also accelerating the training speed. Instead of using SGD optimizer [18], we choose to use Adam optimizer [19] that can adjust the learning rate on each weight parameter, which guarantees effective training.

3 Results and Discussion

3.1 Image denoising Result

We use MNIST dataset to train our Denoising AutoEncoder. We train the AutoEncoder with a 100 batch size input noisy images for 100 epochs. We get the noisy images by manually add some random Gaussian noise to the input images. By trying to get the output images as the origin noiseless images, we get our denoised images in Fig 4. As we can see through the results, the denoised images quality is very good and is almost the same with the noiseless images. Unlike our former work on image compression (with pruning), images generated by AutoEncoder have less Gaussian noise than those images generated by pruning Auto-associated network [17]. It's because in AutoEncoder,

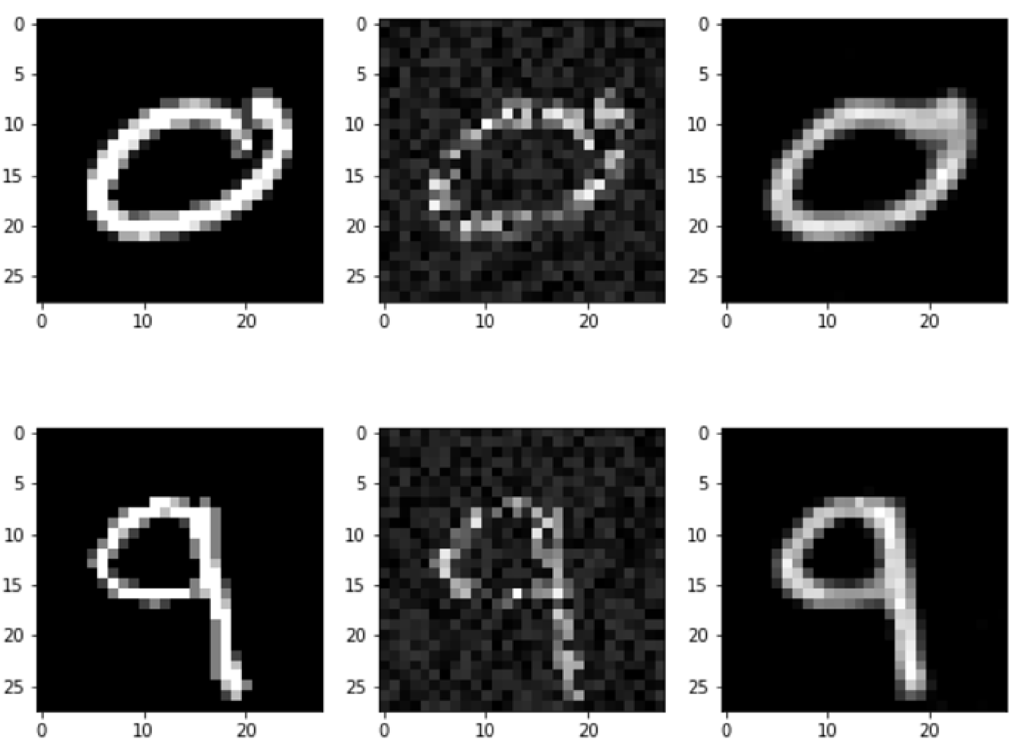

Fig. 4. The first column are the origin images, the second column noise-added images and the third column are the denoising images

we use CNN instead of fully connected layer as CNN has broad views of images and can gain more information than fully connected layers. Besides, in order to see the quantitative result, we use pre-trained neuron network classifier to see how well it correctly classify each input images.

3.2 Comparisons on classification result

We first train a classifier on training part of MNIST dataset of 30 epochs and in order to let it fastly reach a stable point, we use Adam instead of SGD optimizer. From Figure 4 we can see the loss on the training set indicate that our network has reached a stable situation. Then we test the classification accuracy on origin images, noisy images and

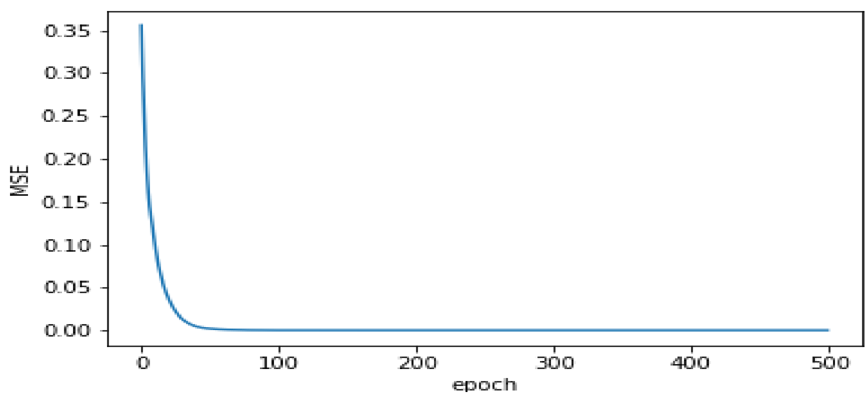

Fig. 5. Training loss of classification on Musk dataset.

denoised images. We assume that the origin images should have the highest classification result as the pre-trained network should have good performance on specific dataset. We also assume that denoised images should have clear higher result over noisy images because we think that added noise can mislead or full the classifier. Origin images, noisy images and denoised images each have 10000 images for testing. We observe the testing accuracy in Table 1. As we can see through the result, the accuracy of denoised images is just slower a bit than the origin images, which

Table 1. Classification accuracy on different set.

Classification Accuracy (%)	Testing
Origin images	98.25
Noisy images	13.68
Denoised images	96.10

means that our encoder preserve the core information of the input images and the decoder can effectively decode the compressed representations without losing too much core information.

4 Comparison

As there didn't have one standard criteria on the quality of denoising images, we could only judge our algorithm by visualizing the different between origin images, noisy images and denoising images.

Some researchers have also work on the images denoising task. Method of Spatial Filtering [20] learn a denoising technique in a traditional way by cleaning up the output of lasers, removing aberrations in the beam due to imperfect , dirty or damaged optics. Time-consuming is its main drawback and our method using encoder can have great efficiency improved. Ways like linear filter and non-linear filter [21] improve the efficiency but makes the denoised images blurring. However, even sometimes images generated might have the blurring problems due to its mean squared cost function, it still have good images result than traditional linear and non-linear filters. Moreover, AutoEncoder with convolution neuron network is one special non-linear filters as the convolution neuron network can be viewed as a big, non-linear and non-convex function. Another advantage that AutoEncoder over all other denoising techniques is that AutoEncoder do not need much data preprocessing and it is an end-to-end training process.

5 Conclusion

We have shown that we can achieve effective image denoising with the method of AutoEncoder network by just feeding noisy images to AutoEncoder and make sure that the output images are similar as the origin noiseless images. This method guarantees that we don't need to do much images preprocessing work and can get the denoised images just from the AutoEncoder. Though the process of encoder is a lossy compression, our method can guarantees the representations generated by encoder have less or no noise in it. Our experiments also shows even little noise of the input images will greatly influence the accuracy of certain neuron network classifier. Moreover, in our cases, the noise is just white Gaussian noise. From its denoising principle, we can see that if we can measure the added noise, this denoising method can be used in removing all kind of digital noise.

6 Future Work

Firstly, the way we modify the difference between noisy images and clean images is simply calculating it mean squared error loss, which will make the generated images blur. Blurriness can be harmful to some recognition application and some future work should be done to solve the problem that images generated by AutoEncoders are blur.

Secondly, those noise added to the origin images are all manually generated, so this method will only focus on removing artificial noise especially of Gaussian noise. However, in real world, it's hard to measure the real noise of images because some noise are not all in Gaussian form. In other words, it's hard to separate noise from images. Hence, some future work should be done on how to generate analog noise that are close to the real noise. If we can get the analog noise and quantitatively measure it then AutoEncoder method still can be a good approach to removing noise from images.

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