A Method of Brain Image Optimization based on an Autoencoder Unet

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Abstract. As data and computer science grows rapidly in the modern era, numerous branches of technology appears one after another, medical imaging is one of them. After medical scans were first conducted as part of medical detection, prognosis, and treatment, methods such as CT, PET, and MRI scans. The precision of medical images is highly demanded for determination of lesion inside the human body. However, due to the variety of noise possibly taking place in the scan, and of how to prevent them each, it is merely impossible to avoid all images from being affected. A solution to this is denoising. Though many denoising methods had been leveled in the past decades, most traditional ones hold the possibilities of losing border information. In response to this specific issue, this paper will focus on using deep learning computation to generate a methods that is highly efficient and keeps images intact at the same time. This involves using unsupervised learning, convolutional neural network, U-net, and autoencode to create a process of the computer learning by itself to improve medical image qualities. With this accomplished, medical image quality can be thrown out of concern for doctors, lifting enormous weight of off their shoulder with the ever-growing population of patients.

1. Introduction
Image digital technology is based on computer, which collects, displays, stores and transmits images, digitizes image information, and optimizes each part separately. Electronic information, computer technology and image digital processing methods are used as the basis of the above imaging technology, and imaging technology is used to effectively complement image information, so as to achieve convenient access to medical image information. It is helpful for clinicians to make treatment plan through image diagnosis, so as to accelerate the rapid development of medical research and new medical technology.

CT is widely used in clinic. However, in the process of CT imaging, the radiation dose produced by CT is more than that produced by X-ray. In the process of taking CT images, the radiation dose to patients is larger than other radioactive images. In conclusion, reducing the radiation dose of CT is of great significance. In recent years, the health risk caused by high dose X-ray radiation has become a major problem in CT. Therefore, low dose computed tomography (LDCT) has become an important research direction. Moreover, unavoidable noise such as motion artifacts and metal artifacts will be introduced in CT imaging. It is of great significance to study a method to improve the quality of CT imaging. Therefore, it is necessary to study a method to remove artifacts caused by low-dose CT
imaging. At the same time, this method should also be able to deal with the artifacts that are difficult to avoid in the normal CT imaging process. Similarly, in many medical imaging technologies, MRI technology is a high-resolution medical imaging technology for human tissues and organs, which can image all parts of the human body from multiple angles and in all directions, and can obtain relatively complete medical image information. However, in the process of image acquisition, storage and transmission, the image will be polluted by random noise of rician distribution, which reduces the signal-to-noise ratio of the image and leads to serious damage. These happen not only on single-channel medical images, but also on multi-channels images in Figure 2 below. It is very difficult for doctors to identify the details of the lesion from the background. Due to the lack of this aspect, the image post-processing is seriously affected, and the accuracy and effectiveness of imaging are reduced. Therefore, image denoising is particularly important. To sum up, the research of medical image denoising has great significance for the future clinical development.

Figure 1. Single-channel and multi-channels medical image with noise and without noise

Traditional image denoising methods are easy to lose image edge information and difficult to save image details when filtering medical MR image noise, which is far from meeting the needs of medical diagnosis. Therefore, there is an urgent need for new research methods and means to solve this problem.

2. Preliminary
To achieve an efficient and precise process of denoising, this paper will describe a method of creating a Convolutional neural network [4, 6]. This process composes of data collection, training, and testing the CNN. Convolutional Neural Network architecture consists of four layers [7, 8].

Convolutional layer is where the action starts. The convolutional layer is designed to identify the features of an image used by different size of kernels. Usually, it goes from the general to specific. Then goes Rectified Linear Unit layer. This layer is an extension of a convolutional layer. The purpose of ReLu is to increase the non-linearity of the image. It is the process of stripping an image of excessive fat to provide a better feature extraction.

Pooling layer is designed to reduce the number of parameters of the input i.e., perform regression. In other words, it concentrates on the meaty parts of the received information. The connected layer is a standard feed-forward neural network. It is a final straight line before the finish line where all the things are already evident. And it is only a matter of time when the results are confirmed.

Net[5], shaped like its name, is a Convolutional neural network that excels in image segmentation shown in Figure 4. Its main differences from traditional neural networks is that its structure is symmetric instead of linear, and has skip connections between the upsampling and downsampling path.
3. Evaluation

3.1. Dataset

One dataset was used to train the system referenced in this paper, Mc. Gill BrainWeb simulated database. The 3D simulated MR images are generated by varying specific imaging parameters and artifacts in an MRI simulator, which starts from a fuzzy digital phantom containing the spatial probabilistic distribution of different tissue types. As an example of the generality of this approach, other brain phantoms were obtained by adding MS lesions (extracted from real MRIs) to the normal phantom, and then we computed signal intensities based on Bloch equations or signal equations, accounting for partial volume according to the scan parameters. Image noise was specified as a percent standard deviation relative to the mean signal intensity for a reference brain tissue. Multiplicative receive intensity non-uniformity (INU) was simulated using fields recovered from real scans, and scaled for different percent sensitivity ranges. A pre-computed SBD was generated by varying specific imaging sequence and artifact parameters. The set of these of parameters was chosen according to the values typically encountered in modern MRI systems. For two anatomical models (normal, and with moderate MS lesions), simulated volumes for three imaging sequences are available online (T1, T2, PD), each with several values of slice thickness, noise and intensity INU levels.

The dataset has been selected from The McGill Montreal Brain Imaging center’s Brain web Database. The database includes data based on two types of MRI data: normal and MS brain lesion. Under these two types, four parameters can be altered with the resulting images, shown in Table 1 below:

| Parameters                  | Range               |
|-----------------------------|---------------------|
| Modality                   | T1, T2, PD          |
| Slice Thickness             | 1mm, 3mm, 5mm, 7mm, 9mm |
| Noise                       | 0%, 1%, 3%, 5%, 7%, 9% |
| Intensity non-uniformity    | 0%, 20%, 40%        |

The modality parameter stands for the pulse sequence exerted when scans are conducted. Different pulse sequence results in different imaging results shown in Figure 3.
Varying slice thicknesses allows the dataset to be altered for different informative details to be viewed. Though the differences described by slice thickness are hard to observe for unprofessionals, they are still useful in certain areas of diagnosis shown in Figure 4.

Certainly, the most important parameter here for us is the noise parameter. The noise parameter allows us to alter images to have a specific percentage of noise. The "percent noise" number represents the percent ratio of the standard deviation of the white Gaussian noise versus the signal for a reference tissue [3] shown in Figure 5. The variations for this parameter allows us to train the Neural Network resulting with both precision and efficiency.

The reason this dataset was selected is for its ability to alter noise levels. With this parameter in place, it is much easier to create corresponding.

3.2. Method

3.2.1. Model. In order to finish the task of denoising without lose detail information, this paper aims to establish a denoise with the help of unet[1]. In general, doctors need to identify many kinds of medical images and make a comprehensive diagnostic results. So our denoise need to deal with different kinds of medical images at the same time[2]. In consideration of the topic that our paper
focus on, we choose many Brain-MRI-Image-Pairs, which include sequences of pictures contain varying degrees of noise for one part of brain. The images with noise will be input to the Unet, after encoding and deconding, a new medical image will be output. Then we used the other image of the same pair which is noise free as label to train out denoise. Finally, when finishing training the denoise net, we choose the label medical image as input and then output a new Brain MRI image. In theory, after training all the datas in our dataset, we will obtain a denosie which can output a clean Brain MRI image whose quality at least not inferior to the quality of the input image. The model framework is shown in Figure 6 below.

![Figure 6. System Framework](image)

**3.2.2. Model Training and analysis.** The implementation of the network is achieved using the deep learning structure Pytorch. It is done using a common tactic, using a pre-trained initializing structure from ImageNet to train. The U-net uses the first five trait extraction layer form VGG-16 Convolutional networks to initialize the weights of its convolutional layers. The entire training process uses SGD back propagation to optimize the entire network. Learning rate is 0.001, image sized are resized into 512*512, every 4190th iteration leads to one reduction in learning rate, and 419000 iterations in total for 100 train epoches. The training results are saved every 20th epoch. The device trained on was ubuntu 16.04, GeForce GTX 2080. The train results for 100 epoches is shown in Figure.7.
As can be seen from the graph, the denoising net came to a stable state during the 90th epoch. The training accuracy and loss would not change too much. Then we could use the trained denoising to generate more clear Brain MRI images.

3.2.3. Image quality evaluation index. **PSNR (peak signal to noise ratio)**

Given a clean image and a noise image with size of $M \times n$, the error of the two is defined as (1):

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \left[ f(i,j) - K(i,j) \right]^2$$  \hspace{1cm} (1)

PSNR is defined as MSE(2):

$$PSNR = 10 \times \log_{10} \left( \frac{MAX^2}{MSE} \right)$$  \hspace{1cm} (2)

Above is the calculation method for single channel images. If the target is a three channel image, there are two general ways in doing so as (3) and (4):

$$PSNR_{RGB} = \frac{PSNR_R + PSNR_G + PSNR_B}{3}$$  \hspace{1cm} (3)

$$MSE_{RGB} = \frac{MSE_R + MSE_G + MSE_B}{3}$$  \hspace{1cm} (4)

4. Experiment

4.1. Single Channel results and analysis

Since MRI imaging varies in Color Scheme, we first validated our solution using single channel images. We trained the network using 4190 images. The 256*256 patches was added with different

![Figure 7. Training process for 100 epoches](image)

**Figure 7.** Training process for 100 epoches
gaussian noise as input and target. The noise was also randomized by the noise standard deviation $\sigma=[0,70]$ for each varying training sample. We can see that the denoising results are favorable in Figure 8.

![Image](image.png)

**Figure 8.** The denoise results with single-channel Brain MRI images

| Noise Level | Noisy Input | Prediction |
|-------------|-------------|------------|
| $\sigma=10$ | 14.28dB     | 20.38dB    |
| $\sigma=20$ | 15.32dB     | 22.76dB    |
| $\sigma=50$ | 15.67dB     | 23.87dB    |
| $\sigma=70$ | 16.01dB     | 25.31dB    |

Table 2. The Denoise Results With Different Noise Level For Single-Channel Images By Psnr

To evaluate the effectiveness of the denoiser, the higher PSNR is, the clearer the image is. It can be clearly seen from the results that the Denoised images form above is more distinct when compared to the Input, the PSNR is also emphasized by the dB values calculated. Label above the images, as the higher the value is, the more distinct the image is. This validate our solution by showing the significant decrease in noise that can be observed from input to result as shown in Table 2.

4.2. Multi-Channel results and analysis

From the results on single-channel Brain MRI images, the denoiser could provide us an high quality image. After that, we tested our method on multi-channels imgae.Eight parts of human brain’s hotmetal pictures were below in Figure 11. The original picture and the clean one without been polluted were available. After inputting the original pictures to denoiser, we obtained denoised picture. Compared with original ones, the new pictures were highly clear with a high PSNR and, to some extent, were almost the same as the groundtruth picture. Our denoiser output the denoised pictures in Fig.9 and the PSNR was calculated and shown Table.3 below.
Table 3. PSNR Results For Multi-channels Images with Noise Input as σ=40

| Index | Noise/dB | Denoise/dB |
|-------|---------|------------|
| 1     | 25.00   | 28.17      |
| 2     | 25.00   | 27.23      |
| 3     | 25.00   | 26.05      |
| 4     | 25.00   | 26.88      |

5. Conclusion
This paper establishes an important method to improve the quality for medical images especially used with human’s brain. Although there are already some ways to accomplish this task, yet image detail loss is very serious. With the help of Unet, we can not only remove noise from polluted images, but also to save the detail information for doctors. All this suggests that our method play an important role for patients’ diagnosis.

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