MRI reconstruction Using dynamic image

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Abstract

In many fields, medical imaging images have been used. Typical technologies include medical segmentation, detection, denoising, and diagnosis. However, MRI reconstruction is specifically classified differently. Because the noise of a particular pattern is random. Also, research is difficult because dynamic data has artifact like motion, breath in MRI reconstruction. To solve these problems, this project apply through the additional network and adversarial learning. As a result, The performance of PSNR and SSIM improved when comparing basic and proposed networks.

1 Introduce

In medical images, MRI, CT, ultrasound, and cell are widely used. Using this image, many people were developing various methods such as finding cancer that doctors cannot find using cancer, counting the number of cells, and segmentation only necessary parts of a medical image, etc.
And among many technologies, we would like to make a medical image reconstruction that lost the spatial information. Because MRI takes a long time to acquire images. for resolving this problem, in the previous study, the performance of the hardware was improved or changing the method for improving the acquire speed. In this methodological method, a restoring image after obtaining a damaged image is widely used for example iterative reconstruction compressed sensing.
In particular, in this semester, I would like to apply reconstruction using deep learning of dynamic MRI dataset which has temporal and spatial features.

2 Related work

MRI image restoration has been studied a lot before. previously,the MRI was reconstructed using the Nyquist–Shannon Sampling Theorem. recently, The state of the art method was the compression sensing method[1], machine learning method like sparse coding However, in compress sensing method, there was a disadvantage in that the time to acquire the image and the required signal were randomly selected. To solve this problem, people recently tried to solve the problem with deep learning, and representative, they improved the image using CNN, GAN, etc. furthermore, in dynamic MRI dataset has combined two information temporal and spatial information that cause artifact. recently, this problem is developing using deep learning such as cardiac dataset recently are using RNN and flowNet.[2]

2.1 Traditional image reconstruction

MRI has got a long time to extract the full image. Because it has to charge magnetic energy. To solve this time problem, research suggests a technical method for diving hardware and software. In the Hardware method in the case of hardware methods, there is a method of dividing the number of coli that make up the MRI into parts[8]. Another method is to reduce the image's image by reducing the

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image's image name field of view(FOV) by reducing the energy of the whole magnetic. However, this method has the disadvantage of having to change the hardware equipment, which is costly. Also, due to the small FOV, the low resolution of the image results in a disadvantage.
Another method of using software is fMRI[3], which is to obtain images by adjusting the pulse of the image. And among the traditional methods is wavelet transform[4], which is a method of reconstruction using spare transform. Recently, the compressed sensing method[1], which uses sparse frequency to restore images more quickly, and digital rendering method, which obtains features in patch units and then reconstructs images using a dictionary[5], have been used.

2.2 MRI reconstruction using deep learning

Recently MRI reconstruction using Deep learning that is aimed to design fast and accurate methods from under-sampled k space data. Among techniques, the convolution neural network (CNN) extract spatial image features[11]. Earlier work uses CNN directly mapping between a zero-filling reconstruction image to full reconstruction image using a deep learning network which proposed an encoder-decoder shape, Cascade shape. In the encoder-decoder shape network[12], it has to skip connection that retains previous encoder features to express features to more learn more features. Another network emphasizes the feature for each level of top-down network shape.[6]
Furthermore, many DLMRI was using stack image to learn feature. However, a dynamic MRI image smaller than a static image[9], because it has two spatial feature information, temporal feature, which has a motion artifact. to solve this problem, the proposed network has 3DCNN that apply stack image from dynamic images. Recently when using recurrent neural network(RNN)[2] that it learning one iterative training step to connect the previous or next image from the dynamic image.
Also, Generative Adversarial Nets apply additional learning to improve quality MRI images[7] and learn noise patterns to remove the artifact. In this method proposed for mapping feature from zero filling image to using additional cyclic loss, another network use segmentation network to improve image quality which is applied by transfer learning, perceptual learning[13].

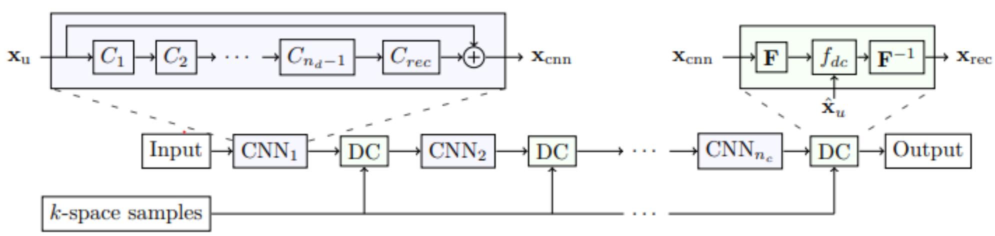

Figure 1: casecade network[11]

3 Method

3.1 Notation problem

We denote the under sampled raw MRI image using the Cartesian sampling mask R, m is input image. then its zero-filling reconstruction S_0 be obtained by the following equation

$$S_0 = F * R(m)$$

F is Fourier operator. reconstruction image $I_s i$ from inverse of reconstruction prosses used inverse Fourier transform follow bottom equation. and we folloing imput image notation is S_i

$$m' = RF^{-1}(S_0)$$

3.2 Baseline Network

ours generate network G consist of two-fold chained networks named WNet that learn noise pattern to remove zero-filling image noise. In which input image has two channels consist of imaginary,

complex values. In this project, we focused on the imaginary channel to calculate real image loss. Furthermore, the generator G network has dense skip connection, concatenate from bottom level encoder feature to high-level feature named unet++[14] to improve image quality.[figure2]
In contrast, the discriminator D attempts to differentiate between the prediction MRI image by removing noise and real full sampling MRI images from MRI dataset. Valia discriminator has 1x1 patch output to classify real or discriminator, however, we set the appropriate size of the patch size which can more growly classify real or fake images to improve image quality.[figure 1]
Lastly both network G, D have bottleneck block has the same architecture as Squeeze and excitation networks[figure 1][10] that has two two stream flow networks. one stream name is squeeze operation, it means that we will only extract and take important information from each channel.[figure 3] In squeeze operation Use one of the most common methodologies, Global Average Pooling (GAP) that can be compressed into channel descriptor. After squeeze operation, in time to Recalibration of important information, This process is called Extension operation, and it calculates channel-wise dependencies. Our entire system is made up of G and D. in next subsection will explain detail about each component.

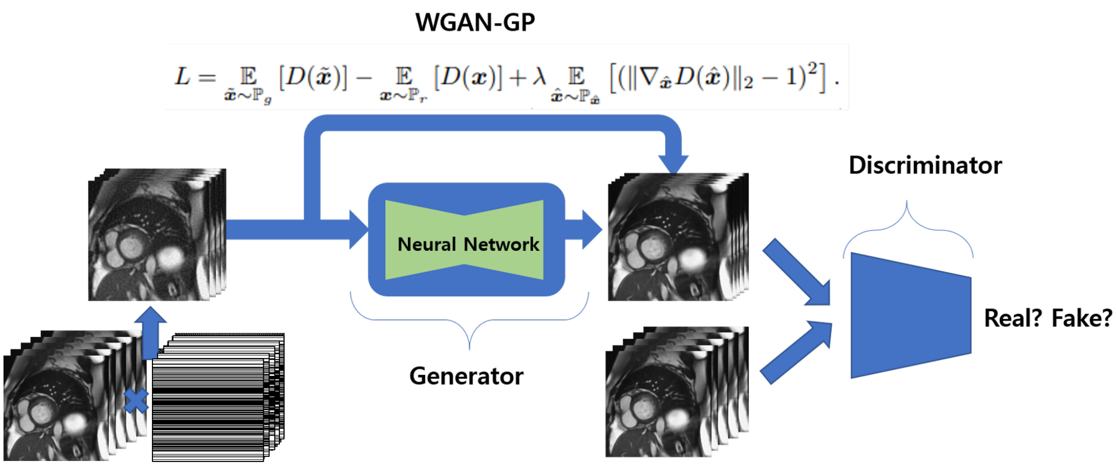

Figure 2: baseline network

3.3 Generative Adversarial loss

Our objective is to train to generate G which makes zero-filling image to reconstruction image. In this we propose three of loss to learning the network., it calculates real image and prediction image each pixel value more closely using root mean square loss which gives a constant weight about 10. (equation) Then, we recover frequency image that applied sampling mask, to improve quality add RMSE another loss.

$$L_{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (S_i - O_i)^2}$$

In the adversarial loss, we select the Wasserstein gan with gradient penalty(WGAN-GP) that stable to training, effective this dataset. In the discriminator part, we apply adversarial loss that compares real images to fake images from network output. We classify image feature space to real or note that is a more detailed measure feature. In lastly discriminator loss was total variation loss which uses a regulation stable that takes advantage of machine learning of dictionary learning. It computes each image variable that image intensity uniform to a real image. [figure 1] So i combine three main loss to Adversairal loss, perceptual loss, RMSE loss and regulization total variation. and each lambda constant weight give 10, 1.

$$R_{TV} = \sum_{i=2}^{n} |S_i - S_i|^2)^{1/2}$$

$$L_{total} = \lambda_1 * L_{RMSE} + \lambda_2 * Ladv + R_{TV}(not\ update)$$

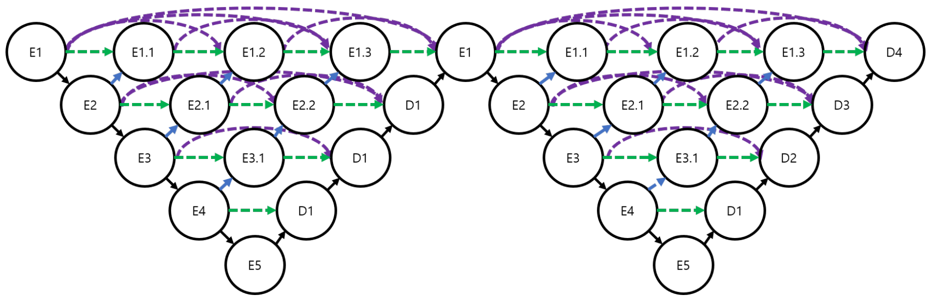

Figure 3: Generator

4 Experiment

4.1 Hpyerparameter

In order to carry out this project, we used the same batch size as four. The optimizer part used Adam to apply the experiment and to speed up learning, the value of the reading rate was reduced by 10 times every 100 days to allow learning from 1e-4 to 1e-2 of the starting learning value. Also, in the case of epoch size, it was fixed at 300 and the generation and discrimination were taught alternately. lastly our network activation function use Tanh function which has output image normalize -1 to 1 value because of imaginary channel and Fourier transform. After training network. we consider an evaluation strategy to which model or loss is more improve the score. Also, an error map was created in addition to the social network to show how much error was reduced.
in the previous MRI reconstruction or many image recovery method denoising, supervision dealiasing exploit PSNR SSIM which easy to summarize value. But in-progress research, this evaluation method is not effective in adversarial loss because prediction image by the result of GAN that each image invents style or shape from real MRI image except images. Besides, an error map was created in addition to the score to show how much error was reduced to check for visual performance improvement.in SSIM equation, μ is mean of image, C is two variables to standard deviation and σ is variance

$$PSNR(x,y) = 10 * \log \frac{MAX_I^2}{MSE} = 20 * \log \frac{MAX_I}{MSE}$$
$$SSIM(x,y) = \frac{(2 * \mu_x \mu_y C_1)(2 * \sigma_{xy} C_2)}{(2 * \mu_x^2 \mu_y^2 C_2}$$

4.2 Result

In order to compare the experiment progress, the first result of the network was compared. To compare the results of each experiment, the mask was compared with x4, x2.2 x3.3 respectively. When we looked at the score from this experiment, we could see that the efficient net was improving, but the performance was poor at x4.
other experiment to compare is to compare how much performance has improved in the form of WNet and simple Unet which are same bottleneck. As a result, we could see that the performance of the WNet was better, but we could see that there was not much difference in the numerical comparison.[See tee Table 1]

The second experiment was conducted by comparing the results of the pixel and patch units in the discriminator. As you can see from the table, we can see in the pixel that the performance in the patch unit is improved more than the result. In the case of an error map, the rate of error is decreasing.

4.3 Conclusion

This project conducted experiments on MRI reconstruction to improve performance. In order to improve performance, the network was constructed by attaching efficient net and net ++ instead of the form of the previously used unit, and in case of a bottleneck, it could be seen that each learned

Table 1: compare PSNR for each Mask

PSNR/SSIM			
Mask	X5	X3.3	X2.5
Zero-Filling	17.668/0.582	19.848/0.667	22.568/0.745
DeepLabV3	-	-	24.917/0.791
Wnet(single)	19.939/0.643	25.436/0.815	27.614/0.866
Efficient Unet++(single)	21.265/0.683	26.393/0.838	27.399/0.862
Wnet	21.640/0.702	26.956/0.852	28.516/0.881
Efficient Unet++	22.681/0.733	27.479/0.862	27.755/0.865

Table 2: compare PSNR for each Mask

PSNR/SSIM		
Network	GAN	PatchGAN
Zero-Filling	22.568/0.745	22.568/0.745
Efficient Unet++	28.516/0.866	27.436/0.861
Wnet	27.755/0.865	29.879/0.909

channel had an orientation to improve performance. Finally, because GAN learning is unstable, he used WGAN to stabilize it.
And to get the loss of discriminator, I knew that the patch unit would be more efficient than the pixel unit, so I made PatchGAN and proceeded with the project. As a result, we could see better performance than the previous STA paper, RefineGAN. However, as the parameters and structure of the overall network grew, the batch size could be reduced batch size was reduced. Also, because of the characteristics of GAN, learning through two networks was not stabilized, and the improvement of the number of parameters in the network was also limited in performance improvement. Finally, through this project, I realized that the composition of a network according to the task is important.

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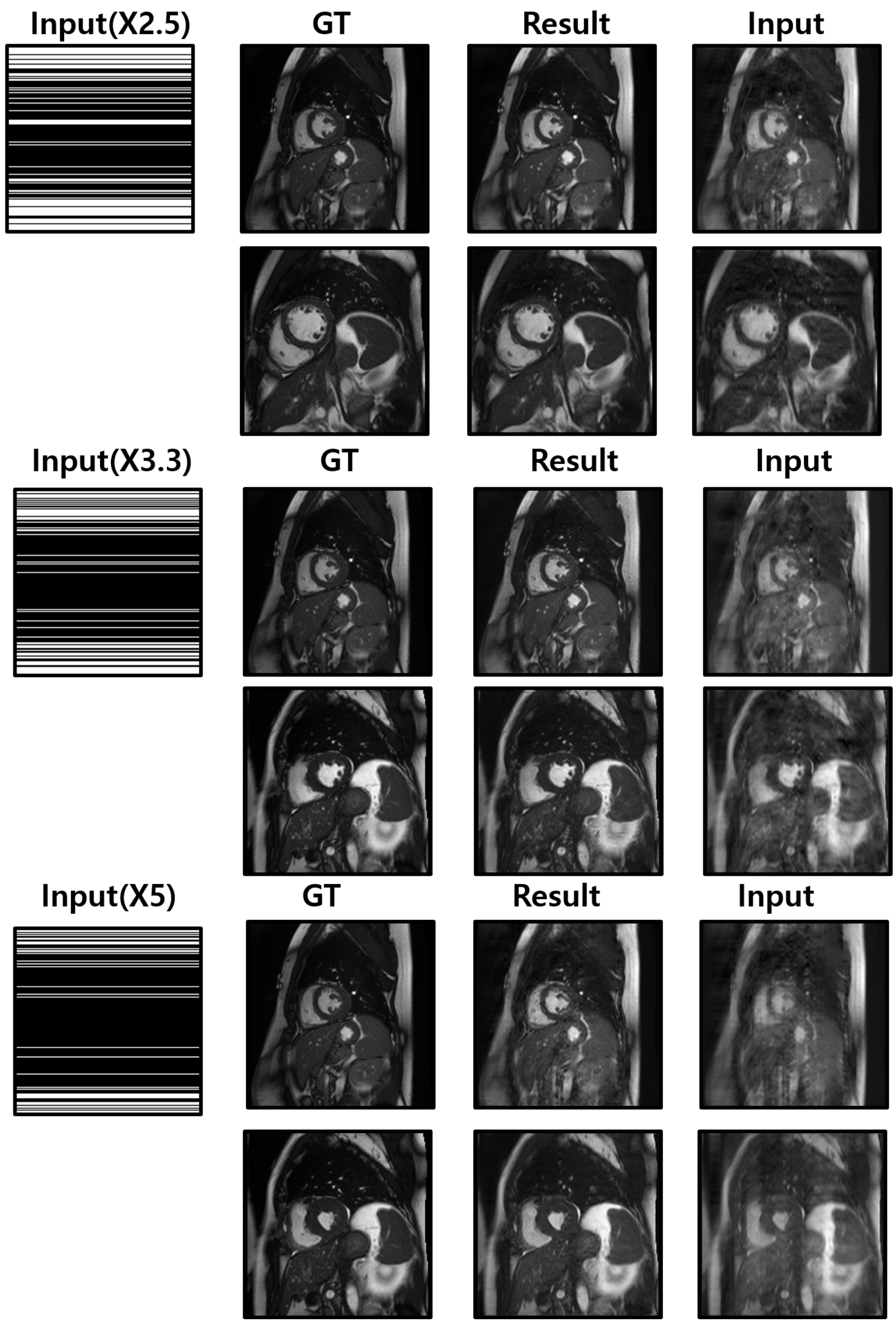

Figure 4: result image

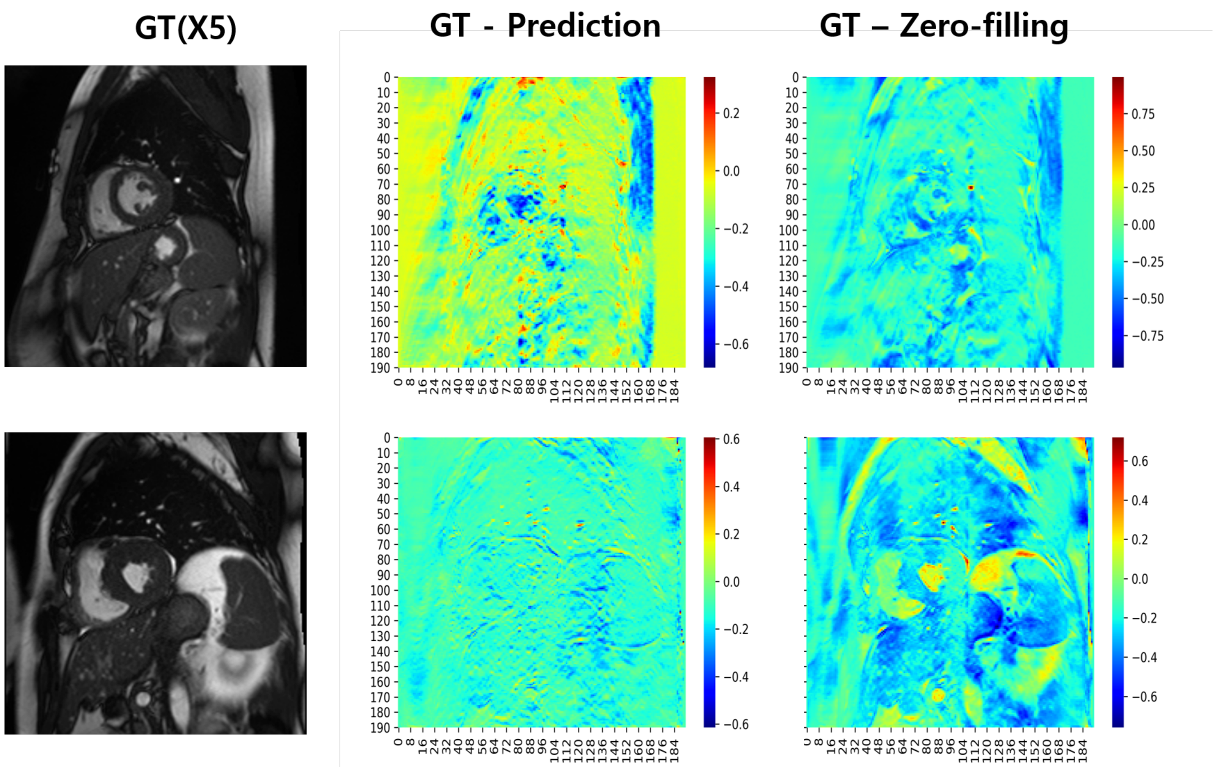

Figure 5: result error map image