A Modified GAN for Compressed Sensing MRI

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Abstract. Magnetic resonance imaging is a commonly used diagnosis method in medicine. Most reconstruction methods are based on the compressed sensing theory, while it is inefficient and time-consuming. In recent years, deep neural networks have developed rapidly. GAN architecture has been widely used in various image tasks after published. This paper proposes a new MRI reconstruction method RISEGAN. The generator uses U-Net structure to extract multi-scale features in the down sampling and up sampling modules. Combined with the residual learning and squeeze excitation blocks, the mapping between the under sampled and the fully sampled image is established. Experiment results show that our method can finish reconstruction with premium quality. Evaluation indicators have also improved.

1. Introduction
Magnetic Resonance Imaging (MRI) technology is one of the most commonly used inspection techniques in modern clinical medical imaging diagnosis. It is accurate, non-invasive and harmless to human bodies. It can detect precise human biological information and is used in many organs such as brain and soft tissue. Although MRI has many advantages, its scanning speed is slow, which cost a long time. In order to obtain a clearer image, sufficient scan time is required. During the scan process, patients have to lie down and be still, which leads to discomfort and motion artifacts, and the utilization efficiency of the equipment is also limited. In order to optimize the scan time and calculation cost, we hope to use less observation data to reconstruct the image as accurately as possible.

The theory of compressed sensing(CS) was first proposed by Candes et al in 2006 [1], which provides a new method of signal sampling. Compared with the traditional Nyquist sampling theorem, compressed sensing can recover the sparse signal better and improve the sampling efficiency. So many MRI methods are based on CS. The concept of Sparse MRI was proposed by Lustig et al. [2], which studied sparse transforms, non-coherent sampling, reconstruction models and algorithms for MRI. In MRI based on compressed sensing, reconstruction model and optimization algorithm are particularly important aspects that determine the reconstruction time and quality.

In sparse MRI, wavelet transform is used as sparse basis, and then scholars successively use Dual Tree Complex Wavelet (DTCWT) [3], Double-Density Complex Wavelet [4], Curvelets [5] and Total Variation(TV) [6] as sparse basis for reconstruction. Fixed sparse basis is used to constrain the image but usually can’t make full use of the sparsity of the image, resulting in bad image quality. After that, many researchers began to study the adaptive sparse representation represented by dictionary learning.
However, dictionary learning needs to learn a kind of images, which usually takes a lot of time and reducing reconstruction speed.

In order to reconstruct MR image faster and better, the optimization algorithm also plays an important role. In Sparse MRI, Nonlinear Conjugate Gradient Descent Algorithm (NLCG) is used to solve the optimization problem. This algorithm is slow and computationally expensive. After that, Iterative Shrinkage Thresholding Algorithm (ISTA) [8] is proposed, which has simpler structure and lower complexity. On the base of the ISTA, Split Augmented Lagrangian Shrinkage Algorithm (SALSA) [9] is derived. The original unconstrained optimization problem is transformed into a constrained optimization problem by variable separation [10]. The alternative direction method of multipliers (ADMM) is also used [11]. This method is used to deal with image problems based on TV constraints later. The representative algorithms are Fast Total Variation Deconvolution (FTVD) [12] and Reconstruction from Partial Fourier (RecPF).

Traditional MRI imaging methods have the following problems. Firstly, the widely used fixed sparse basis may not be able to capture the complex tissue structure well, affecting the imaging quality. Secondly, it may take a lot of iterative steps to optimize the objective function, which is often time-consuming. Finally, most of the algorithms are in pursuit of higher indicators and usually leads to excessive image smooth and affects the visual perception of the image.

Because of the development of deep learning, neural network has been used to solve various image problems including classification, segmentation, object detection and other fields. Recently, deep learning has been introduced into CS-MRI to solve the limitations of traditional methods. Wang et al. [13] first used deep learning in CS-MRI and used convolution neural network (CNN) to establish the mapping between the zero filled image and the fully sampled image. The ADMM net [14] defined he data flow graph absorbing the idea of the ADMM to optimize the MRI model based on CS.

IanJ. Goodsell et al. proposed the Generative Adversarial Networks (GAN) in 2014 [15]. Subsequently, GAN architecture has been widely used in various image tasks and made breakthrough results. DAGAN of Imperial University of technology [16] uses the idea of GAN for MRI. The generator network uses the architecture of U-Net for reconstruction. Subsequently GANCS is proposed [17], Mardani et al. fused LSGAN and CycleGAN together. The real and imaginary parts of k-space data are fed in two channels to train the network simultaneously.

Because of the multi-resolution characteristics, Ronneberger et al. proposed the U-Net architecture [18]. It is widely used in biomedical image processing. The main characteristic of U-Net is using the cascaded down sampling layers to obtain the exponential growth receptive fields and integrate multi-scale details. Residual learning was proposed by He Kaiming to solve the problem of vanishing gradient in very deep networks [19]. It could be used in all kinds of networks because it can accelerate the convergence of networks. The Inception module was proposed in GoogleNet [20], through several parallel convolution layers to obtain the feature maps of different resolutions and increase the width of the network at the same time. In the Squeeze-Excitation block proposed by Hu, Jie, etc, attention mechanism [21] is introduced to explicitly modeling the interdependence between convolution feature channels to improve the representation quality of the network. The network performs the recalibration of feature channels and use global information to selectively emphasize strong information features and suppress less useful features.

RISEGAN (Residual-Inception-SEblock-GAN) proposed in this paper has the following innovations: (1) SE-block is used in the generator network to perform attention mechanism on each level of features and recalibrate the information between channels. (2) In the process of down sampling, several convolution kernels of different sizes are used to improve the ability of feature extraction under different receptive field sizes, which improve the quality of details in images. (3) The model combined with residual learning. It is applied in input and output as well as down sampling blocks to accelerate the process of network convergence and feature extraction. (4) Performed experiments on public datasets with MICCA 2013 dataset and compared with the results of DAGAN model. The experimental results show that the proposed model has better results in the test set. The reconstruction quality has been improved compared with DAGAN.
2. Related work

2.1. GAN network
GAN network has been utilized in various fields after proposed 2014. It consists of a generator \( G \) and a discriminator \( D \). The target of \( G \) is to map the hidden variable \( Z \) to a given distribution of real data to deceive the discriminator \( D \). The goal of discriminator \( D \) is to distinguish the real data \( x \) from the fake data generated by \( G \). In the process of confrontation game, the generator and discriminator train each other. The training process of GAN can be expressed in equation (1):

\[
\min_G \max_D \mathbb{E}_{x \sim p_{l(x)}}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log (1 - D(G(z)))]
\]

\( p_{l(x)} \) is the distribution of real data, \( p_z(z) \) is the distribution of hidden variables. In this paper, \( G \) network is used to establish the mapping between under sampled image and fully sampled image. \( D \) network is used to determine whether the input image is the result of \( G \) network or a fully sampled image.

2.2. Inception
Inception is an architecture proposed in GoogleNet. This structure uses convolution kernels of different sizes to extract parallel features at the same time. Then concatenate channels to achieve multi-scale feature fusion. This method not only increases the width of the network, but also fuses the features of different receptive fields. In the reconstruction of MRI, the main problem is the restoration of detailed features. Most MR images contain detailed information in multiple scales. So we combine the Inception structure in the network to improve the reconstruction quality. In the experiment, \( 3 \times 3, 5 \times 5, 7 \times 7 \) convolution kernels are used to extract the feature information at different scales, so that the structure information can be captured better in the process of down sampling.

2.3. Residual learning
Residual learning is proposed by He et al. It can be used in deeper networks to solve the problem of gradient vanishing in network training, which makes it possible to train deeper networks and avoid over fitting. Shortcut is used to add connections between network layers and avoid network degradation. On the other hand, it makes the network learn the residual instead of the whole mapping relationship. Therefore, the network is easier to train and can converge faster. In this paper, we will make a long residual connection between the input and the output, so that the model can learn the difference between the under sampled image and the fully sampled image. It just needs to learn the missing part of the image features. In addition, the short residual connection is used in the features extraction stages of each down sampling block to reduce the training difficulties and improve the accuracy.

2.4. U-Net
U-Net was first proposed by Olaf Ronneberger et al. The network structure includes a shrinking path for capturing context and a symmetric expanding path for precise positioning. It works pretty good in medical image segmentation. Because of its structural characteristics, it also has good performance in image super-resolution, inpainting and other issues. In the process of down sampling, the feature maps of each scale is connected to the corresponding level in the up sampling path. These skip connections can directly pass the features of the encoders to the decoders. The decoder fuse features and get more precise results. So we choose U-Net structure as the generator.

2.5. SE Block
Squeeze-Excitation block use attention mechanism to allocate computing resources to the most useful part of the features. This is to improve the quality of network representation by explicitly modeling the interdependence between convolution feature channels. This mechanism allows the network to perform the recalibration of feature channels and learn to use global information to selectively emphasize the features useful and suppress the useless features. An SE block consists of three parts:
squeeze, excitation and instantiation. The structure of SE block is shown in figure 1. The significance of a single channel is described by a global average pooling layer. Then channel importance is extracted by a bottleneck structure. Finally, the weights are multiplied with the original channels. This block can be integrated into various networks and improve the model. Although a small number of parameters will be used, the cost is acceptable compared with the improvement. In this paper, SE block will be added before the output of each up sampling and down sampling blocks to adjust features of this level.

![Figure 1. Structure of the SE block.](image)

3. Method

3.1. Traditional MRI method

Suppose \( x \in \mathbb{C}^N \) is a vector stacked by a 2 dimension complex MR image which has a length \( N = N_x N_y \). The problem of traditional compressed sensing MRI is to recover the vector \( x \) from an under sampled vector \( y \in \mathbb{C}^M (M \ll N) \) in K space [22]. \( x \) and \( y \) satisfy \( y = F_u x \) where \( F_u \) is an under sampled Fourier transform matrix. Because this is an ill-conditioned problem, we must use its prior information to recover \( x \). The problem can be transformed into the following optimization problem, i.e. equation (2).

\[
\min_x R(x) + \lambda \| y - F_u x \|_2^2
\]

Where \( R \) represents the regularization constraint for \( x \). \( \lambda \) is a regularization coefficient. In compressed sensing, \( R \) is usually the norm of \( x \) in a sparse domain. The traditional solution needs to find a suitable optimization algorithm for iteration.

3.2. Reconstruction with deep learning

In recent years, with the development of deep learning, there has been a method using deep neural network to reconstruct the image [23]. A deep network can be used to directly establish the mapping between the under sampled zero-filled image \( x_u = F_u^H y \) and the fully sampled reconstructed image. It can be solved by optimizing the objective function in equation (3).

\[
\min_x \| x - f_{cnn}(x_u; \theta) \|_2^2 + \lambda \| y - F_u x \|_2^2
\]

\( \theta \) is the parameter of the neural network that can be trained by gradient descent algorithm.

3.3. Network structure

The whole structure of the networks used in this paper is shown in figure 2. The generator is a modified U-Net. In the left side, there is cascaded down sampling blocks, and right side is the symmetrical up sampling blocks. There are skip connections and concatenation to connect feature maps under a same scale. A skip connection is also used between input and output to learn the missing information.

The structure of i-th down sampling block is shown in figure 3. In the down sampling blocks, the output of the (i-1)th block is followed by three parallel convolution layers of 3 * 3, 5 * 5, 7 * 7 kernel size. Set strides=2 to down sampling. Then concatenate three outputs similar to Inception. After that, two 3 * 3 convolution kernels are used to extract further features. Other branch is used to form a residual block. Because the number of channels increases after concatenation, 1 * 1 convolution is
used to adjust the channels and fuse feature maps of different scales. Finally, a SE block is used to reweight channels for attention mechanism. Its output is the output of i-th down sampling block.

![Figure 2. Structure of the generator.](image)

**Figure 2. Structure of the generator.**

![Figure 3. Layers in the i-th down sampling block](image)

**Figure 3. Layers in the i-th down sampling block**

![Figure 4. Layers in the i-th up sampling block](image)

**Figure 4. Layers in the i-th up sampling block**

The structure of i-th up sampling block is shown in figure 4. In the up sampling block, use transpose convolution for the output of the (i-1)th level and set strides=2. The output of the i-th level down sampling block is also an input to obtain all features at this scale. Then two convolution layers of 3 * 3 kernels are used to extract features. Finally, the attention mechanism of SE block is used to adjust the channel weights, and the output is the output of the i-th up sampling block. Behind all convolution layers in the network, a BN layer is connected to adjust the data distribution and a leaky ReLU function is used as the activation function.

3.4. loss function
To train the generator, its loss function consists of four parts as follows:

$$\min_{\theta} \alpha \|x - \hat{x}\|_2^2 + \beta \|vgg(x) - vgg(\hat{x})\|_2^2 + \gamma \|fft(x) - fft(\hat{x})\|_2^2 + \log(1 - D(\hat{x}))$$

(4)

$x$ is a fully sampled image. $\hat{x}$ is the output of the generator. The calculation flow diagrams of losses are shown in figure 5. The first term is Mean Squared Error(MSE). It is used to measure the pixel difference between $x$ and $\hat{x}$. The second term is perceptual loss proposed by Li FeiFei et al [24]. It measures the difference of high-level features of $x$ and $\hat{x}$ to ensure the structural similarity between the images. The third term is the loss of frequency domain. It is the MSE of the Fast Fourier transform of $x$ and $\hat{x}$ to ensure the similarity of frequency domain information. Because the data is sampled from the frequency domain, the consistency of frequency information is also necessary. The last term is the adversarial loss calculated by the discriminant network. The purpose of the generator is to minimize the loss to fool the discriminant network. The adversarial network is a normal network similar to a binary classification network. There are 10 convolution layers. A single neuron is connected by a fully connection layer. The activation function is Sigmoid and the output is the probability that the image is a real image.
4. Experiments and results

4.1. Dataset
The network uses the MICCAI 2013 grand challenge dataset for training and testing. There are 16104 T1 weighted MR images for training, 5024 for validation, and 9854 for testing and taking the mean value as the result. The original data is fully sampled, so we make under sampling of 1D and 2D Gaussian distribution for masks. The sampling rates are 10%, 20%, 30% respectively to achieve 10x, 5x, 3.3x imaging speed improvement. Figure 6 figure shows the generation of training data. A zero filled image is generated from 10% Gaussian mask multiplied on the frequency of the fully sampled image. We used data augmentation to increase data and help training.

![Figure 6. Generate training data](image)

4.2. Training parameters
The model is implemented by TensorLayer library and trained on GTX1080 with 12GB memory. VGG network uses pre-trained weights on ImageNet that are publicly available on the internet. Some hyper-parameters used in training are as follows: the batch size is set to 8 and the initial value of learning rate is $10^{-3}$. We used a 0.5 times learning rate decay for every 5 epochs but no less than $10^{-6}$. The Adam optimizer is used for optimization with a parameter 0.5. For the loss function of the generator, $\alpha$ is 16, $\beta$ is $10^{-5}$ and $\gamma$ is 0.1. The average training time of each model is 12 hours.

4.3. Experimental results
This paper compares 6 methods: Zero Filling (ZF), DAGAN, RSEGAN (including Residuals, SE blocks but not including the Inceptions), RIGAN (including Residuals, Inceptions but not including the SE blocks), ISEGAN (including Inceptions, SE blocks but Residuals are not included) and RISEGAN (including all blocks). Among them, RSEGAN, RIGAN and ISEGAN are ablation experiments to explain the specific utility of each block in the model. Results use three commonly
used evaluation indicators: MSE (Mean Squared Error), PSNR (The Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) [25]. Bold in the table is the best result.

### Table 1. MSE results.

|        | 1d-10 | 1d-20 | 1d-30 | 2d-10 | 2d-20 | 2d-30 |
|--------|-------|-------|-------|-------|-------|-------|
| ZF     | 0.32970 | 0.17758 | 0.15134 | 0.23744 | 0.17977 | 0.13155 |
| DAGAN  | 0.16552 | 0.08206 | 0.08091 | 0.08961 | 0.07121 | 0.05155 |
| RSEGAN | 0.12293 | 0.05985 | 0.05902 | 0.07355 | 0.06060 | **0.04252** |
| RIGAN  | 0.12388 | 0.05934 | 0.05752 | 0.07278 | **0.05681** | 0.04286 |
| ISEGAN | 0.12133 | **0.05838** | 0.05760 | 0.07113 | 0.05914 | 0.04267 |
| RISEGAN| **0.12071** | 0.05844 | **0.05671** | **0.07072** | 0.05686 | 0.04253 |

### Table 2. SSIM results.

|        | 1d-10 | 1d-20 | 1d-30 | 2d-10 | 2d-20 | 2d-30 |
|--------|-------|-------|-------|-------|-------|-------|
| ZF     | 0.77026 | 0.84595 | 0.87661 | 0.63116 | 0.71744 | 0.80140 |
| DAGAN  | 0.95723 | 0.98684 | 0.98704 | 0.98199 | 0.98806 | 0.99386 |
| RSEGAN | 0.97478 | 0.99285 | 0.99317 | 0.98786 | 0.99134 | 0.99582 |
| RIGAN  | 0.97423 | 0.99298 | 0.99349 | 0.98817 | 0.99251 | 0.99587 |
| ISEGAN | 0.97524 | 0.99339 | 0.99349 | 0.98863 | 0.99188 | 0.99582 |
| RISEGAN| **0.97562** | **0.99341** | **0.99373** | **0.98883** | **0.99267** | **0.99595** |

### Table 3. PSNR results(dB).

|        | 1d-10 | 1d-20 | 1d-30 | 2d-10 | 2d-20 | 2d-30 |
|--------|-------|-------|-------|-------|-------|-------|
| ZF     | 28.4104 | 33.8631 | 35.3203 | 31.2509 | 33.7829 | 36.5667 |
| DAGAN  | 34.4450 | 40.6222 | 40.7174 | 39.8708 | 41.8705 | 44.7634 |
| RSEGAN | 37.0120 | 43.3710 | 43.4803 | 41.6518 | 43.3862 | 46.4733 |
| RIGAN  | 36.9491 | 43.4629 | 43.7008 | 41.7410 | **43.9187** | 46.4379 |
| ISEGAN | 37.1336 | **43.6180** | 43.6855 | 41.9703 | 43.6164 | 46.4379 |
| RISEGAN| **37.1758** | 43.6134 | **43.8471** | **41.9919** | 43.8906 | **46.4998** |

MSE results are shown in table 1. Compared with ZF and DAGAN, new model and ablation experiments have less MSE values. In 1D 10%, 30% and 2D 10%, the complete RISEGAN achieves the best results. In other sampling patterns, three ablation models all perform the best MSE in a certain sampling pattern. However, there are only small differences among these models. Smaller MSE may cause the reconstructed image to be too smooth. Therefore, further judgments need to be combined with other indicators.

Observing the SSIM results in table 2, RISEGAN has the best results in all sampling patterns. Compared with ZF and DAGAN, each ablation experiment also has some improvement. Smaller sampling rate means less available data and the improvement is more. SSIM improves 0.19 under 1d-10% sample pattern. The improvement is relatively small when the sampling rate is higher and the information is sufficient.

Observing the PSNR results in table 3, RISEGAN achieves the best results in most sampling patterns. When it is not the best result, it is also close to the highest value. Compared with DAGAN, each ablation experiment has an improvement of more than 1.5 points. It shows that the proposed...
RISEGAN can complete the reconstruction task well and improve the NMSE, SSIM and PSNR values. When the computing resource is sufficient, you can choose the RISEGAN model with the most parameters to get the best result.

Figure 7 shows the reconstruction results of the zero filled image in the above figure. The first row are the outputs of the networks and the second row is the error maps of the outputs. The brighter color corresponds to a higher error. The result of DAGAN has lower PSNR and the difference is higher in the error map. Compared with DAGAN, the results of RIGAN, RSEGAN, ISEGAN have more details. The PSNR value is higher 2 points than DAGAN. However, these three results are similar. RISEGAN has the best result. It has the highest image quality and the best PSNR value.

![Figure 7](image)

**Figure 7. Output PSNR values of networks**

### 5. Conclusion

In this paper, we use a new neural network RISEGAN to establish the mapping between the under sampled data and the fully sampled image to accelerate MR imaging. Compared with the DAGAN architecture, SE block is integrated to the model for attention mechanism between channels, combined with the Inception structure to achieve multi-scale features extraction. Besides, we use the residual learning to accelerate the training process. Results show that the proposed model can achieve better reconstruction image quality than previous methods. In the future, we can do further research in 3D and dynamic MRI.

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