3D MRI Reconstruction Based on 2D Generative Adversarial Network Super-Resolution

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1 Introduction

Our study proposes a two-steps super-resolution reconstruction method to achieve the three-dimensional reconstruction of MRI based on the two-dimensional gradation. The method we put forward has achieved good visual effects and sufficient high-frequency details.

In our research, we propose to perform super resolution reconstruction of MRI from the two-dimensional level. The super resolution reconstruction of MRI usually uses a three-dimensional convolutional neural network but including a high time cost and insufficient memory resource allocation. Therefore, we utilize the two-dimensional convolutional neural network to perform super-resolution reconstruction of MRI. We propose two super-resolution reconstruction steps. In the first reconstruction work, we propose a residual multiscale module with an attention mechanism generative adversarial network(RMAM-GAN)[1] to perform super-resolution reconstruction of half the number of MRI slices. Aiming at the noise and missing values in the reconstructed MRI, we propose a noise module enhanced generative adversarial network(nESRGAN) as the second super-resolution reconstruction network. Our method completes the MRI super-resolution reconstruction based on the two-dimensional gradation. Moreover, the restoration of high-frequency information is superior to traditional three-dimensional super-resolution methods. The obtained high-resolution MRI can help doctors obtain more brain information, which has particular significance for diagnosing and predicting brain diseases.

2 Main methods

Our research is based on MRI slices to carry out MRI reconstruction to reduce training costs and memory allocation problems. Considering the characteristics of the 3D pixel matrix of MRI, we can obtain slices in three orthogonal planes[2] by traversing the three dimensions of MRI. We set a scale factor of 2 in the experiment. According to the matrix characteristics of MRI, obtaining the entire MRI requires half the number of slices to be prepared as a condition for reorganization. Moreover, although the number of reconstructed slices is only half in the three dimensions,

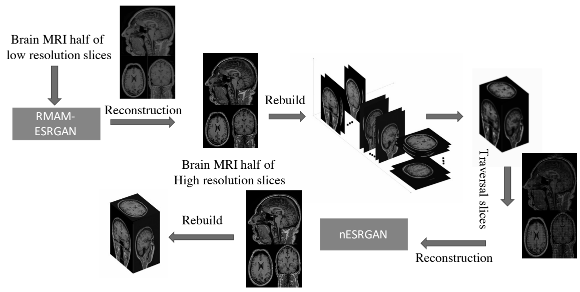

Figure 1 Main Reconstruction Steps.

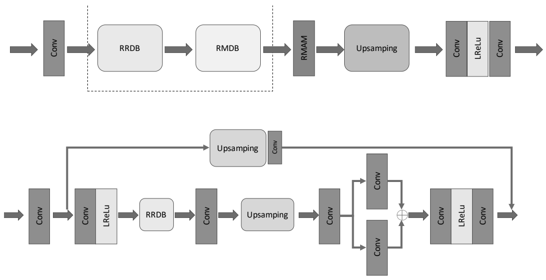

Figure 2 RMAM-GAN(above) and nESRGAN(below).

MRI can still be reconstructed based on the particularity of MRI. Due to the insufficient number of slices, there are many noises and missing values in the reconstructed MRI. In the beginning, we consider that the reconstructed slice has much high-frequency information, which can be interpolated and repaired by surrounding pixel values.

However, interpolation repair will only restore more low-frequency information and enlarge the influence of noise and missing values, resulting in more blurred areas. Therefore, we build a second network to perform a second super-resolution reconstruction of the entire MRI to restore the overall high-frequency information and details. We take the new slice as a low-resolution image and then perform the super-resolution reconstruction of the new network. Finally, we recombine the reconstructed MRI slices to obtain a new high-resolution MRI.

Figure 1 shows the specific steps. We use RMAM-GAN to perform MRI super-resolution reconstruction in the first reconstruction. RMAM-GAN can obtain MRI high-resolution slices with affluent details. After that, a second super-resolution reconstruction is

Table 1 Comparison of 2D and 3D.

	PSNR ↑	SSIM ↑	LPIPS ↓
Gaussian Blur(LR)	19.2471 ± 1.7245	0.4353 ± 0.0859	0.4661 ± 0.0268
3D-SRCNN	16.5874 ± 0.3925	0.5352 ± 0.0273	0.4007 ± 0.0101
3D-SRGAN	21.7050 ± 1.3896	0.7397 ± 0.0132	0.2021 ± 0.0113
ours	**23.9249 ± 0.2631**	**0.8804 ± 0.0067**	**0.1220 ± 0.0043**

performed through nESRGAN to supplement and restore more high-frequency information. The architecture of the two networks is shown in Figure 2.

3 Result and Comparison

After the reconstruction from two networks, we compare the performance of MRI super-resolution reconstruction. Firstly, we compare the details before and after the MRI reconstruction in the spatial domain. Figure 3 shows the pixel distribution of the image reconstruction. It can be seen that the distribution of the MRI slice before reconstruction is quite different from that of the original high-resolution MRI slice, and the reconstructed MRI slice fits the distribution of the original high-resolution MRI slice. The content is close to the authentic MRI slice, and there are minor differences in details, but it is close to the authentic MRI slice.

Traditional MRI three-dimensional super-resolution reconstruction in deep-learning generally uses CNN or GAN to perform[3]. We also compare our method with three-dimensional-based super-resolution methods. As is shown, Table 1 shows the comparison of each method. It can be seen from the table that our method maintains advantages in image evaluation compare to 3DSRCNN and 3D-SRGAN. In addition, 3D-SRGAN and our method are better than other methods (figure 4). In terms of texture details, our method is superior to 3D-SRGAN.

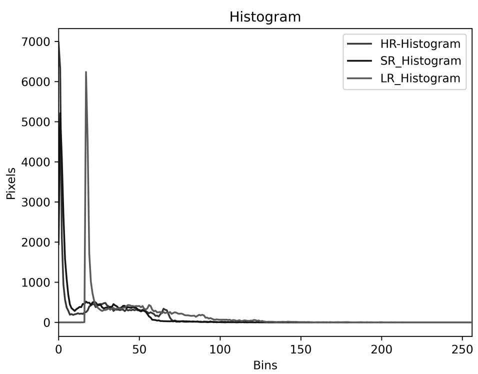

Figure 3 Comparison of pixel histogram.

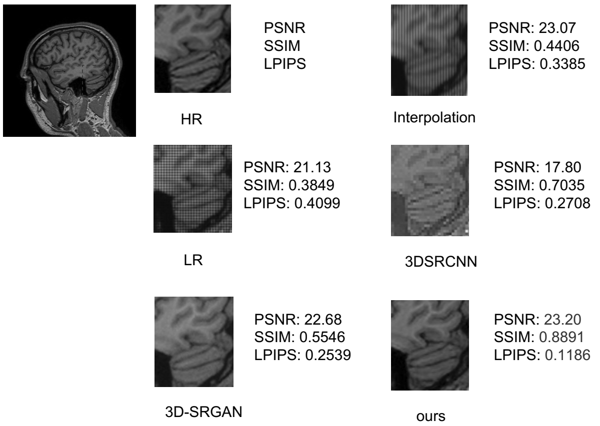

Figure 4 Comparison of interpolation,2D and 3D.

4 Conclusion

Our study proposes a two-steps super-resolution reconstruction method to achieve the three-dimensional reconstruction of MRI based on the two-dimension. The method we put forward has achieved good visual effects and sufficient high-frequency details, which can improve the efficiency of diagnosis within a limited time.

References

[1] Lan, Rushi, Long Sun, Zhenbing Liu, Huimin Lu, Cheng Pang, and Xiaonan Luo. "Madnet: A fast and lightweight network for single-image super resolution." IEEE transactions on cybernetics 51, no. 3 (2020): 1443-1453.

[2] Figueiredo, Oscar. "Advances in discrete geometry applied to the extraction of planes and surfaces from 3D volumes." PhD diss., Verlag nicht ermittelbar, 1999.

[3] Pham, Chi-Hieu, Aurélien Ducournau, Ronan Fablet, and François Rousseau. "Brain MRI super-resolution using deep 3D convolutional networks." In 2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017), pp. 197-200. IEEE, 2017.