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Super resolution reconstruction of PET images based on deep learning

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Abstract: *PET-CT is a high-end medical imaging technology that can detect tumors in the early stage, and has been widely used in clinical practice.Obtaining high-quality images is a prerequisite for doctors to make a correct diagnosis.For PET itself, how to continuously improve its resolution is a challenging problem.In this study, Generative Adversarial Networks (GAN) combined with Wasserstein distance and gradient penalty technology was used to achieve PET image super-resolution reconstruction.The experimental results show that the structural similarity of the final image reaches more than 60%.*

Keywords: *PET, super resolution, deep learning, GAN*

1. Introduction

PET (Positron Emission Computed Tomography) is one of the most advanced clinical imaging devices in nuclear medicine.PET imaging works by labeling a positron-emitting radionuclide, such as an F-18, to a compound that is involved in the blood flow or metabolism of human tissue. The radionuclide labeled with a positron-emitting compound is injected into the subject.PET is the only new imaging technology that can display the activities of biomolecular metabolism, receptors and neurotransmitters in vivo. It has been widely used in the diagnosis of a variety of diseases, efficacy evaluation, or GAN function research and new drug development.The advantages of high sensitivity, high specificity, whole body imaging and high safety make PET popular.

However, PET still has the disadvantages of poor image resolution, unclear anatomical structure and high noise, and in many cases, it cannot obtain satisfactory anatomical information.In order to solve these shortcomings of PET, many people have improved its image quality: including hardware and software aspects.In terms of hardware, there are methods such as prolonging scanning time and increasing tracer dose, but they only play a certain degree of noise reduction effect, and cannot improve the resolution.Therefore, the innovation in software is particularly important, especially the use of neural network to improve the quality of PET image, is the current research hot spot. SRGAN (super resolution generated adversarial network) is a landmark work of perception-driven super resolution proposed by Ledig [1]. SRGAN adopts a new perceptual loss function, which utilizes network features of VGG as content loss function to replace the previous MSE loss function.This method is the first attempt to apply GAN [2] framework to SR.In order to improve the resolution of the image, the perceptual loss and the adversarial loss pair are used to build the model in SRGAN.

Although the existing GAN-based super resolution methods can be used to generate real texture information, they are difficult to achieve the ideal super resolution reconstruction effect. Park [3] developed a GAN-based SISR (Single Image Super Resolution) method, and proposed a binary discriminant under the SR framework to improve the Image quality

Kennedy [4] improved PET/CT image fusion by using a hybrid method of image reconstruction and super resolution. Super resolution algorithm was adopted to combine multiple PET images to improve the resolution. Ahn [5] used two low-dose CT images of respiratory period to carry out super-resolution reconstruction of three-dimensional PET images and carry out super-resolution reconstruction of the images. Hu [6] can also achieve super resolution reconstruction of PET-CT by using dictionary learning and random forests. Krzysztof [7] proposed an efficient PET-CT image reconstruction strategy based on highly sparse ridge let. The analytical sampling mode is combined with PET signal perception

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to improve resolution and minimize scan time.

Wang [8] enhanced SRGAN from three key aspects: network architecture, discriminant improvement and perceived loss.First, the team used a variant of enhanced SRGAN (ESRGAN) to improve the generator network. In the generator, a residual dense block (RRDB) without normalization was used, and other strategies such as residual scaling and 0.1MSRA were also used.In the aspect of discriminant, the correlation idea of Relativistic GAN is introduced. The discriminant judges the relative value rather than the absolute value, and judges the related fraction rather than the absolute fraction.Perceived loss is improved by constraining features before but not after the activation function.

In this paper, WGAN-GP is used to train the images obtained by using five processing methods respectively, so as to achieve super resolution reconstruction of PET images.This method can greatly improve the quality of PET images.

2. Methodology

The experimental process includes data preprocessing (including down-sampling and enlargement) and GAN network training.

2.1 Down-sampling

In the down-sampling, the research group adopts the method of interpoint sampling, that is, a pixel value is taken at every other point and input to the output image. The formula is

$$I\_out(i, j) = I\_in(2*i, 2*j) \tag{1}$$

The result is a low-resolution image that is 1/2 the length and 1/2 the width of the original image, as shown in Figure 1.

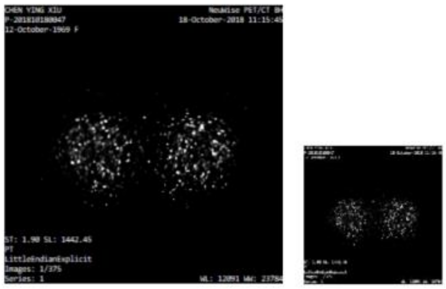

Figure. 1 The results of the following sampling by the interpoint sampling method

2.2 Enlargement

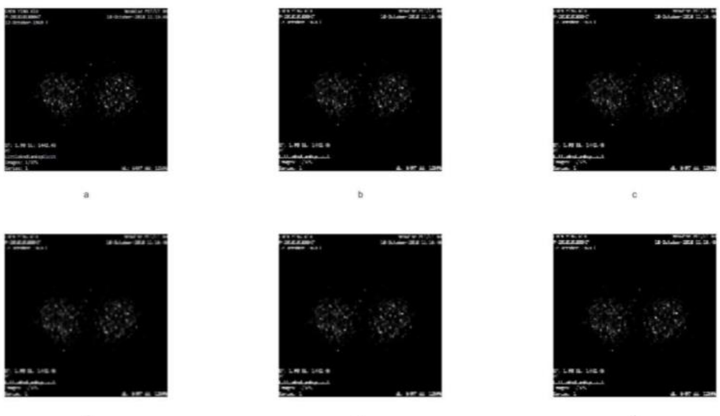

Figure. 2 a is a low-resolution image without preprocessing. b, c, d, e f are all images amplified by a after down-sampling. The methods adopted are Zero Fill Interpolation(ZFI), Nearest Neighbor Interpolation, Bilinear Interpolation, Bicubic Interpolation, New Edge Neighbor Interpolation (NEDI).

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In this paper, the existing super resolution algorithm is used to enlarge the low resolution image to the same size as the image before down-sampling before input to the neural network.In this paper, 5 classical SR algorithms are used to amplify the low-resolution images after sampling respectively, and the corresponding processed low-resolution images are obtained.The five classical algorithms are zero fill interpolation, nearest neighbor interpolation, bilinear interpolation, bicubic interpolation and new edge-oriented interpolation.These images obtained by different super resolution algorithms have different characteristics, as shown in Figure 2. Next, these amplified images are used as input to train corresponding GAN models for training.

2.3 GAN model

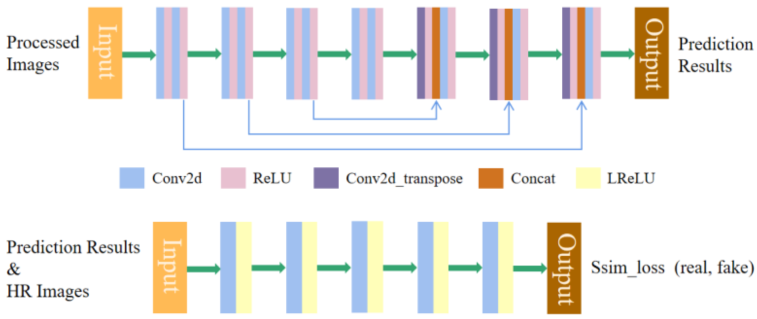

Figure.3 The architecture of the generator and discriminator in the GAN model.

WGAN-GP [9] model was adopted in this paper.The design of generator and discriminator is based on the work of Lyu [10] and has been improved. The specific generator structure is shown in Figure 3.The network consists of seven convolution blocks joined together, and three jump joins, thus enabling the join of feature maps in the previous block to feature maps in the next block.Inside the first four blocks, the function interface of the 2D convolution layer is used to complete the convolution operation first, and then the ReLU function is used to activate it.The operations of deconvolution, ReLU, Contact, Convolution and ReLU are used in the internal order of the last three blocks.For the discriminator, the concrete structure is shown in Figure 3, which collectively consists of five blocks, each containing the convolution and the Leaky-Relu operation.The details of generators and discriminators are listed in Tables 1 and 2.

So far, the experimental model of moving target tracking system has been established. From the model, we can know that the state equation of the system is linear, and the observation equation is nonlinear.

Table1. Structural details of the generator

	Block1	Block2	Block3	Block4	Block5	Block6	Block7
Filters	32 32	64 64	128 128	256 256	128 128	64 64	32 32

Table2. Structural details of the discriminator

	Block1	Block2	Block3	Block4	Block5
Filters	64	128	256	512	1
Kernel_size	3	3	3	3	3

Table3. Structural details of the VGG19

ConvNet Configuration								
3-64 3-64	MP	3-128 3-128	MP	3-256 3-256 3-256 3-256	MP	3-512 3-512 3-512 3-512	MP	3-512 3-512 3-512 3-512

In this paper, Adversarial Loss, Gradient Loss, Mean Squared Error, Perceptual Loss, and the Structural Similarity are adopted to measure the effectiveness of the model.In addition, the trained

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VGG19 model was adopted during the experiment, and the specific structure of the model is shown in Table 3.

3. Results and discussion

Data from 8 patients (a total of 3430 initial low-resolution images) were input as the training dataset. One set of data was selected as the original input data, and the training process was evaluated.

In the training processing, the optimization algorithm carried out 20 iterations, and the image structure phase obtained in each iteration was obtained, as shown in Fig. 4.

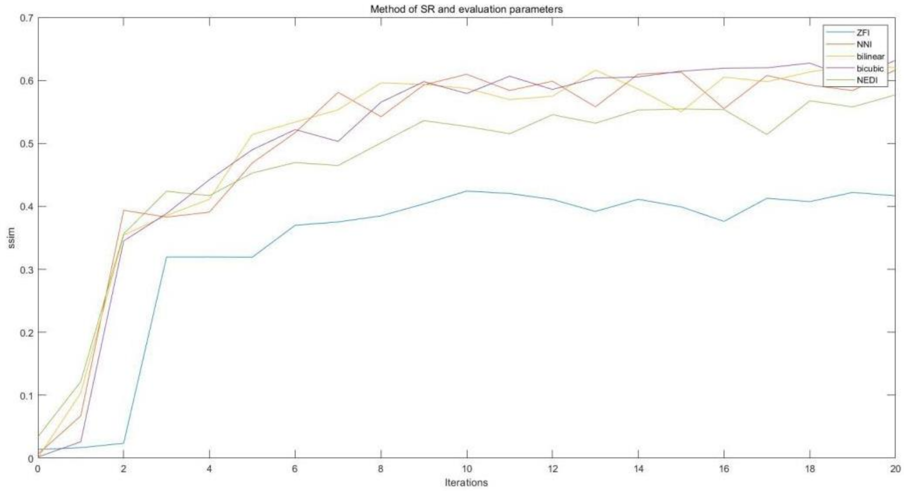

Figure. 4 The curve of structural similarity (SSIM) with the number of iterations

The times of iterative training 0,5,10,15,20 were taken to demonstrate the effect of the training process, and the mean square error (MSE) and structural similarity (SSIM) were used as the evaluation parameters, as shown in Table 4.As can be seen from the table, after only 20 generations of training, its structural similarity has significantly improved, from less than 1% to more than 60%.Among them, the structural similarity of only the results using zero-fill interpolation is only 40%, which is speculated to be because the enlarged image with zero-fill interpolation loses a lot of details of the original image, so the training effect of its data set is not good. However, it can be seen that the training effect is more satisfactory.

Table4. The results obtained by taking 0,5,10,15,20 iteration numbers for training

Method of SR	Evaluation parameters	Iterations				
		0	5	10	15	20
Zero fill interpolation	MSE	715.0417	101.8885	100.1137	63.5501	62.0614
	SSIM	0.014024	0.319212	0.424136	0.399077	0.416612
Nearest neighbor interpolation	MSE	984.0126	104.7672	61.9612	42.7708	43.1679
	SSIM	0.006521	0.468837	0.609510	0.612933	0.616559
Bilinear interpolation	MSE	961.5433	51.9422	32.6862	116.4703	24.8182
	SSIM	0.000814	0.513914	0.587077	0.549800	0.620332
Bicubic interpolation	MSE	1187.5754	67.3338	35.1614	41.6990	36.7643
	SSIM	0.002090	0.489779	0.579031	0.614467	0.631852
New Edge neighbor interpolation	MSE	797.4300	71.2791	52.0942	66.2103	47.8360
	SSIM	0.034047	0.452802	0.526713	0.554438	0.576892

4. Conclusion

In this paper, a GAN-based super resolution PET reconstruction method is proposed. First, the initial high-resolution images are down-sampled by the interpoint sampling method, and then the existing five super resolution reconstruction algorithms are used to amplify the down-sampled low-resolution images, and the low resolution images with complementary priors are obtained.Each super -resolution algorithm preserves the image features to some extent.Combining all of these super-resolution algorithms creates data sets with complementary priors.Then, the WGAN-GP network is used to generate super-resolution prediction results for five different preprocessed low-resolution images.Experimental results show that after 20 sessions, it can achieve good results.

The data set of complementary priors can be used for training, so that the GAN can get more comprehensive information and the trained model can get clearer PET images.Although the existing training results are still satisfactory, the structural similarity of the generated images only reaches more than 60%.In the future, the model will be re-optimized and the parameters will be adjusted appropriately through the training results to achieve a higher accuracy.

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