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A Novel Algorithm for Better Interpolating Low Resolution Medical Images

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Abstract

High-resolution magnetic resonance (MR) images with fine structure features are important not only in research but also in medicine. However, because of the relatively long imaging duration, acceleration techniques are still in high demand. Learning-based Super-Resolution (SR) methods for MRI have also gotten a lot of interest, thanks to the rapid growth of machine learning techniques. To improve reconstruction quality, we integrate these two fields with Single-frequency Excitation WideBand (SE-WB) MRI and super-resolution (SR) Generative Adversarial Network (GAN).

Keywords: Deep Learning; Super-Resolution; Magnetic Resonance imaging;

1. Introduction

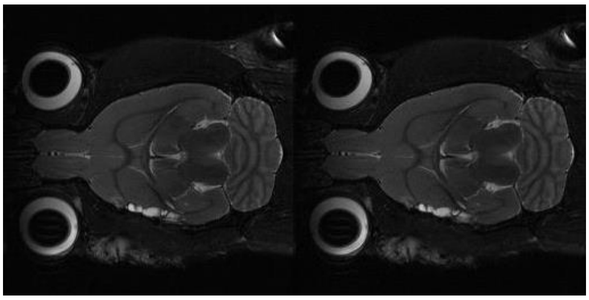
Recent advances in digital medical imaging technology have expanded the use of digital images. Existing methods provide considerations for increasing complexity. It is especially essential in various modalities of chest radiography, mammography, PC tomography, and medical imaging and CAD frameworks. Various improvement techniques are abstract, problem-organized processing techniques in which a particular algorithm is associated with a plan for a particular application. Broadly speaking, x-rays can be used to map the internal structure of the human body. This is used to recognize internal problems. This is an imaging modality commonly used to check for fractures and other related issues. Magnetic resonance imaging (MRI) has several advantages, including: B. Non-radiation and non-ionizing properties. It is becoming a widely used imaging technique for visualizing body structure and function. However, MRI usually takes tens of minutes. And this flaw reduces the potential of the application. Therefore, it is important to reduce the time required. Compressed sensing (CS) MRI algorithms [1,2,3,4] are becoming possible solutions. And E.L. SEWB MRI [4] Wu proposed by Wu is one of the possible methods. It reduces the number of phase encoding steps and utilizes an increased sample rate with a separation gradient applied along the phase encoding direction, thereby tilting the horizontal read orbit. The result is a parallelogram k-space coverage with the same sample density as standard imaging. This speeds up the imaging process and can result in the loss of only some of the radio frequency signals.

In addition, the computational power has improved significantly these days, making deep learning (DL)a viable solution to many problems. On the other hand, the resolution of MR images has a positive correlation with the required time. Therefore, the SR-DL method can also be used to accelerate the MRI process.
Many learning-based methods, especially the latest convolution method [5,6,7,8,9,10], significantly improve image quality. For example, the Super Resolution Generative Adversarial Network (SRGAN) [9] proposed by

Christian Ledig reconstructs more high frequency image signals than these methods without a discriminator. This means better visual quality, even though it has a lower PSNR compared to a generator called SRResNet. In addition, a method called Enhanced Deep Residual Network (EDSR) [10], improved by SRResNet, improves accuracy, which is an important element of medical imaging. Therefore, we are trying to apply the EDSR architecture to SRGAN to see if it provides higher accuracy while maintaining good visual quality. Figure 1 shows that the improved SRResNet achieves nearly the same performance on PSNR and SSIM with lower parameters.

1.1 Interpolation of Images

Insertion is the most common way of concluding the assessments of a capacity at positions lying between its examples. It achieves this interaction by fitting a constant capacity through the discrete data tests. This licenses input regards to be evaluated at optional situations in the data, not just those described at the example centers. While testing produces a ceaseless transmission capacity signal from one that is band obliged, introduction expects an opposite work: it reduces the transfer speed of a sign by applying a low-pass channel to the discrete sign. That is, addition replicates the sign lost in the testing system by smoothing the information tests with an introduction work. The course of addition is one of the significant exercises in picture handling. The picture quality astoundingly depends upon the used interjection procedure. The addition procedures are apportioned into two arrangements, deterministic and measurable insertion strategies. What makes a difference is that deterministic interjection procedures acknowledge specific variance between the example centers, for instance, linearity assuming there ought to emerge an event of direct insertion. Factual interjection strategies unpleasant the sign by restricting the assessment blunder. In rundown, we consolidate WB MRI and SRGAN with EDSR and reproduce low-goal WB MR pictures into high-goal ones. Meanwhile, we apply GAN architecture to our model trying to obtain images with high-frequency details restored, an example that was super-resolved with a 2× up scaling is shown below in Fig 1(a)Original (b) 2× ISRGAN



.Fig.1.The2×ISRGANsuper-resolved image(b) is pretty similar with the original one (a) even in the detail structure

2. Related Works

2.1. Compressed Sensing MRI

MRI, while its many advantages, has a severe restriction in terms of rather poor data collecting speed. By lowering the amount of k-space measurements directly obtained by the machine, compressed sensing-based MRI is one of the most successful strategies for accelerating magnetic resonance acquisition [1,2,3,4]. CS theory demonstrates how filling up the missing Fourier coefficients of k-space with sufficient optimizations can result in accurate or even flawless reconstruction. The FDA recently approved CS MRI for a number of major suppliers [11]. In order to increase patient comfort by speeding up the data collecting process, more CS MRI technologies are projected to be adopted in clinics. SE-WB accelerate the imaging process by increasing *k*-space coverage and maintaining spatial frequencies with zig-zag trajectory. After processing such as removing the data sampled during the buffer intervals and regridding the *k*-space according to the trajectory. The *k*-space became zig-zag form whose unsampled triangular regions were zero-filled.

2.2. Convolutional Neural Network

Recently, with the rapid development of machine learning, deep neural networks have become widespread in SR research. In addition, many computer vision problems are caused by a specially designed CNN architecture. Also, many powerful models have been proposed. A brief introduction follows. Compare with VDSR [12] proposed by J. Kimetto et al. SRResNet [9] successfully mitigates the effects of timing and memory issues caused by the need for bicubic interpolated images as input. Also, He.et al. You can achieve excellent performance simply by using the ResNet architecture of. [13] No major changes. However, this model was developed to solve these problems with various attributes such as image classification and detection. Consequently, it very well may be unacceptable to apply ResNet engineering straightforwardly to low-even out PC vision issues, for example, super-resolution..As portrayed above, EDSR [10] is thereupon proposed. It eliminates the Batch Normalization (BN) layers of remaining blocks in SRResNet. Since these BN layers standardize the elements, they lessen the reach adaptability from networks by normalizing the highlights, so it is smarter to dispose of them. Also, this change saves around 40% of memory utilization during preparing. As such, this permits engineering to become further and more extensive and keep up with lighter model size simultaneously. In the paper, the model is planned by setting with B = 32, F = 256 which address profundity (the quantity of layers) and width (the quantity of component channels) separately and accomplish better execution.

2.3. Loss

To enhance the Peak Signal-to-Noise Ratio, many SR networks use Mean Square Error (MSE) as their loss function (PSNR). By comparing the performance of SRResNet trained with these two loss functions, it is shown that L1 loss gives better convergence than L2.Triplet loss is commonly employed in applications such as face recognition and categorization. Anchor, positive, and negative input are the three parameters. The fundamental idea is to make the anchor move closer to positive input while also moving away from negative input. And MSE is commonly used to compute the distance. Meanwhile, a margin value of 0 to 1 is employed to improve classification skill as the value increases. However, this can make training more challenging.

3. Material and Method

3.1. Research Purpose

To find and verify most suitable model architecture and parameters for improved SRResNet. Then we adjust loss function to apply to SRGAN in order to achieve better performance.

3.2. Research Method

First, we remove the BN layers of residual blocks in SRResNet. And verify whether it performs as well as origin SRResNet with WBMR images super-reconstruction. If so, the lower hardware load due to smaller structure allows deeper or wider model expansion. Then these condstudy following is to find the most suitable depth and width of modified SRResNet for WBMR images.

Inspired by triplet loss, we adjust L1 loss in to the following form:

$$L(X_A, X_N, X_P) = \sum_{i=1}^{N}[|x_i^A - x_i^P| - \alpha|x_i^A - x_i^N|]$$

Where $x^i{}_A$, $x^i{}_P$ and $x^i{}_N$ are the SR images, HR images and WB HR images

Low Resolution (LR) images into High Resolution (HR)ones. A weight is added to prevent model from over focus on secondary aim. Furthermore, we remove the margin value of origin triplet loss to avoid rising of training difficulty.

In addition to L1 loss, we add an operand of distance between anchor and negative input to let model learn SR reconstruction better by getting away from negative input. However, the main target is still reconstructing Low Resolution (LR) images into High Resolution (HR) ones. A weight is added to prevent model from over focus on secondary aim. Furthermore, we remove the margin value of origin triplet loss to avoid rising of training difficulty.

Last, we need to figure out the best weight for the modified loss. Then applying these to the new SRResNet called Improved SRResNet (ISRResNet) as the generator might achieve better performance than the origin SRGAN. The work flow how we train SRGAN is shown in Fig.3.

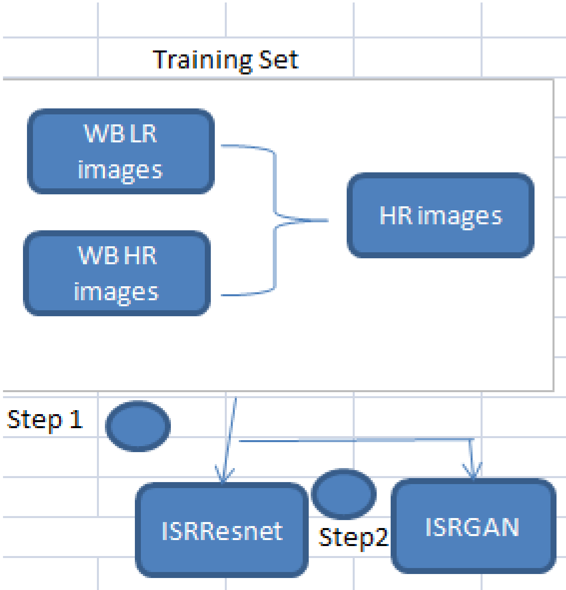


Fig. 3.Training steps. Train ISRResNet to obtain initial weight of generator in ISRGAN first. Then train ISRGAN with the weights.

3.3. Training Set

Due to the low time and reproducibility caused by artifacts, movements, etc., it is not only nearly impossible to collect training data from hospitals and most research centers, but it is also non-generated through iterative imaging projects. It's realistic. Because of these difficulties in collecting MR images, a training set is used. To get the WB-HR k-space, use the WB style k-space mask at the origin HR-MRI k-space. Fourier transform use then to get the HR and WB-HR training sets. And LR training set can be generated by down-sampling HR training set with bicubic method. All these steps are summarized and shown in Fig. 5.

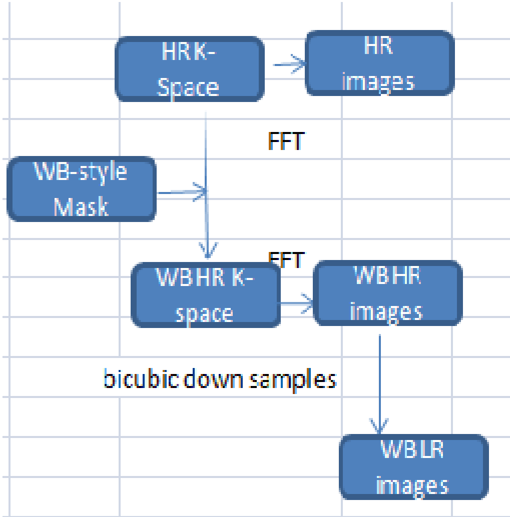


Fig.4.Steps of creating our HR,WBLR and WBHR training sets where FFT means Fourier Transform.

Through this work flow, our training set is created with 312 RARE images of rat brain whose images are selected from the middle 3 slices of whole brain MR from 104 cases each. And we cover WB-style k-space mask like Fig. 6. on these images' *k*-spaces to generate simulated WB MR images. Then, we down-sample them with bicubic method to get low-resolution version of WB MR image. All the original images of training sets' resolution are 256*256 pixels.

And we follow the same steps to create 78 images testing set with other 26 cases.

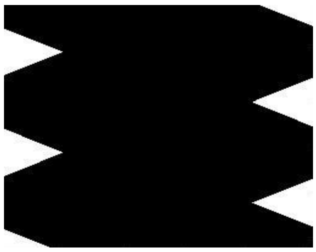


Fig. 5.WB-style k-space mask.

We use it to get rid of specific area of HR MRI *k*-space to obtain WB-style k-space.

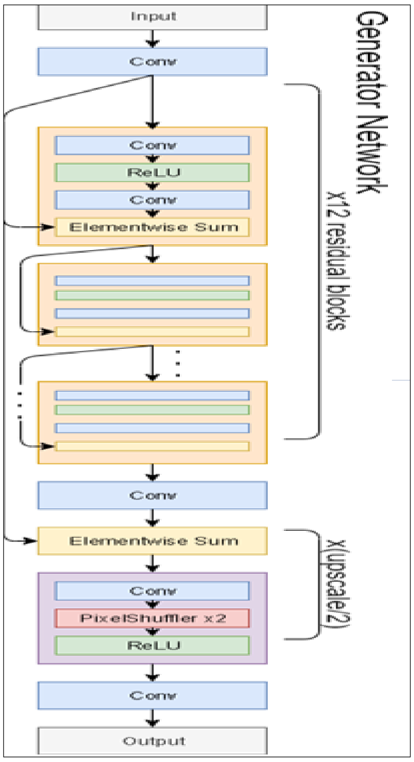
Results:

Refer to table. 1. We can see that ISRResNet performs as well as the original SRResNet with the same size of residual blocks. Also, we test different numbers of residual blocks and convolution feature channels to figure out the best depth and width of ISRResNet. ISRResNet contains 12 residual blocks with 64 convolution feature channels not only perform as well as SRResNet but also saves almost half training time consume. So we decide to choose this setting as our SRGAN's generator. The complete architecture is shown on Fig. 6.

Model name	nb	nf	PSNR	TimePro portion
SRResNet	16	64	35.45	1
ISRResNet	16	64	35.51	0.69
	20	64	35.504	0.8
	24	64	35.517	0.91
	16	96	35.501	1.07
	16	128	35.514	1.33
	12	64	35.511	0.54
ISRResNet_NAC	12	64	35.49	0.57

Table1.Performance of different setting of residual blocks base on Peak Signal-to-Noise Ratio(PSNR).

As describe above, we decide to use 12 residual blocks and 64 convolution feature channels in our ISRResNet. Moreover, Table 2 shows ISRResNet achieves better performance with our triplet type loss in spite of MSE loss and why we set 0.1 as our loss weight. Moreover, it improves the original SRResnet as well. This indicates that our loss can be more powerful function for other models.



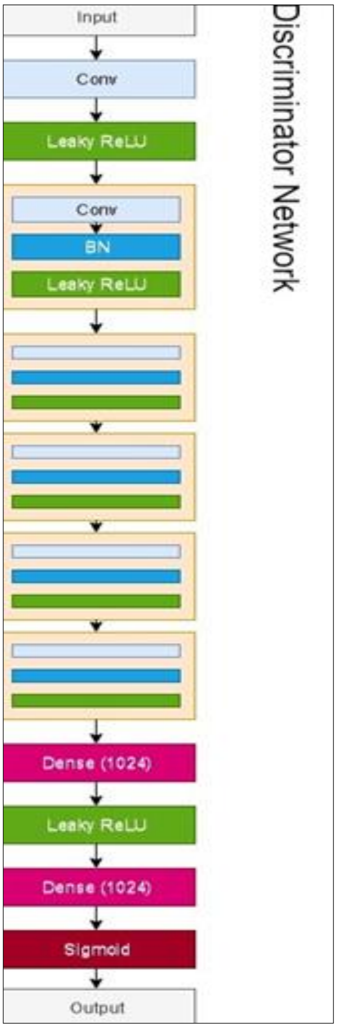


Fig.6.Architecture of Generator and Discriminator Network with corresponding numbers of residual blocks and denselayer width.

Model	PSNR	SSIM
ISRResNet(α=0.3)	35.627	0.907
ISRResNet(α=0.2)	35.647	0.907
ISRResNet(α=0.1)	35.648	0.907
ISRResNetwithL1 loss	35.51	0.906
SRResNet(α=0.1)	35.659	0.908
SRResNetwithL2loss	35.45	0.906

Table 2.Performance of ISRResNet and SRResNet with different loss setting.α represents weight of our triplet type loss.

4. Conclusion

Many people attempt to build new types of blocks, organise diverse blocks and connections, or simply extend or deepen models in order to improve performance. There are still more parameters that can be tuned for certain tasks. We'll use the terms triplet loss and negative training set interchangeably. It improves SRResNet without requiring any complex adjustments. For other models, this could be a viable option.

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