Single Image Super-resolution via Dense Blended Attention Generative Adversarial Network for Clinical Diagnosis

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Abstract

In clinical diagnosis, doctors are able to see biological tissues and early lesions more clearly with the assistance of high-resolution (HR) medical images, which is of vital significance for improving diagnosis accuracy. In order to address the issue that medical images would suffer from severe blurring caused by lack of high-frequency details, this paper develops a novel image super-resolution (SR) algorithm called SR-DBAN via dense neural network and blended attention mechanism. Specifically, a novel blended attention block is proposed and introduced to dense neural network (DenseNet), so that the neural network can concentrate more attention to the regions and channels with sufficient high-frequency details adaptively. In the framework of SR-DBAN, batch normalization layers in the original DenseNet are removed to avoid loss of high-frequency texture details, final HR images are obtained by deconvolution at the very end of the network.

Furthermore, inspired by the impressive performance of generative adversarial network, this paper develops a novel image SR algorithm called SR-DBAGAN via dense blended attention generative adversarial network. SR-DBAGAN consists a generator and a discriminator, the generator uses our proposed SR-DBAN to generate HR images and try to fool the discriminator while the discriminator is designed based on Wasserstein GAN (WGAN) to discriminate whether the input is a real HR image or a generated SR image. Moreover, we use the L1-Charbonnier loss and the GAN loss to guide training, further enhancing the sharpness of generated HR images. We deployed our algorithms on blurry prostate MRI images, and experimental results showed that our proposed algorithms have generated considerable sharpness and texture details and have a significant improvement on the peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM), respectively, compared with mainstream interpolation-based and deep learning-based image SR algorithms, which fully proves the effectiveness and superiority of our proposed algorithms.

Keywords: Single image super-resolution; Dense neural network; Attention mechanism; Generative adversarial network

1. Introduction

In medical clinical diagnosis, with the assistance of high-resolution (HR) medical images, doctors are able to see biological tissues and early lesions more clearly, which is of considerable beneficial of diagnosing and treating diseases\cite{1, 2, 3, 4}. However, HR medical images are hard to obtain due to limitations of imaging hardware and noises in the wild. Compared with improvements which rely on hardware evolution, using super-resolution (SR) algorithms for fast blurry...
images SR is characterized by stable universality, high efficiency and low cost\cite{5,6}. With the rapid development of artificial intelligence, image SR algorithms have been widely used in medical images\cite{7}, computer-aided diagnosis and other fields, which is one of the research hotspots in the field of medical images processing.

Image super-resolution(SR) refers to reconstructing corresponding high-resolution(HR) images according to its low-resolution(LR) counterparts\cite{8}. According to the number of input frames, SR can be classified into single-image SR(SISR) and multi-image SR(MISR). This work focuses on SISR. According to different principles, image SR algorithms can be divided into three categories: interpolation-based, model-based and deep learning-based algorithms\cite{9}. Interpolation-based algorithms such as bicubic interpolation are characterized of high computational efficiency, but they are easy to lose high-frequency texture details. Model-based algorithms such as the maximum a posteriori probability(MAP) algorithm\cite{10} use prior information to constrain the solution space whose performance is improved compared to interpolation-based algorithms. However, there is little prior information that can be effectively utilized when the size of the input image is small, causing poor performance. Learning-based algorithms can be divided into compressed sensing-based algorithms\cite{11} and deep learning-based algorithms\cite{12}. Compressed sensing is a technique to acquire and reconstruct signals efficiently, by finding solutions to underdetermined linear systems. This is based on the principle that, through optimization, the signal sparsity can be exploited to recover it from far fewer samples than required by the NyquistShannon sampling theorem\cite{11}. Yang et al. first introduce compressed sensing into the field of image SR, and propose a algorithm based on sparse representation which simultaneously learns the HR dictionary and the LR dictionary so that the HR image blocks and their corresponding LR image blocks have the same sparse coding in their own dictionaries\cite{11}. Algorithms based on sparse representation can better preserve edge textures but are difficult to learn higher-level abstract features, furthermore, they are incapable when the scaling ratio of SR is large.

Propelled by the blooming development of big data, big datasets such as ImageNet, COCO etc. have made it possible to train deep neural networks, promoting the prosperity of image SR algorithms. Dong et al. first propose a deep learning-based algorithm SRCNN(Super resolution using convolutional neural network)\cite{12}, which can be divided into three stages, namely feature extraction, nonlinear mapping and reconstruction to actualize end-to-end learning. Convolutional neural network-based algorithms no longer explicitly learn an external dictionary, but implicitly learn the convolution kernel parameters of the middle layers of the network, which have better generalization and expression ability. On the basis of SRCNN, Kim et al. propose VDSR(Very Deep Super Resolution Algorithm) and draw the conclusion that the deeper the network, the better the performance\cite{13}. Compared with SRCNN, VDSR deepens the network layers, adds a skip connection to learn the residual between input and output images which is beneficial of improving the gradient vanishing and network degradation problems. Both SRCNN and VDSR need to be upsampled via bicubic interpolation before they are fed into the network which means that the convolution is performed on the HR image space, resulting in complicated calculation and low efficiency. In order to address the aforementioned issue, Shi et al. and Dong et al. propose ESPCN(Efficient sub-pixel convolutional neural network)\cite{14} and FSRCNN(Fast SRCNN)\cite{15}, respectively. FSRCNN and ESPCN perform direct convolution on the LR image space whose size is smaller than that in SRCNN and VDSR, and perform sub-pixel convolution or deconvolution at the very end of the network to obtain final HR images. Compared with SRCNN and VDSR, ESPCN and FSRCNN achieve significant improvements on efficiency and reconstruction results.

Deep neural networks are vulnerable to suffer from gradient vanishing or network degradation problems. He et al. propose ResNet(Residual Net)\cite{16} by stacking multiple residual blocks, which alleviates the gradient vanishing and network degradation problems caused by networks depth deepening. Ledig et al. propose SRRResNet(SR Residual Network) based on ResNet\cite{17}. SRRResNet introduces abundant global and local skip connections, so that the majority of low-frequency texture contents can be directly transmitted to the end of the network through skip connections, with which bring the
advantages of alleviating gradient vanishing and enhancing feature propagation. Dense neural network (DenseNet) proposed by Huang et al.\cite{18} introduces dense skip connections to neural network, so that the output feature maps of any layer can be transmitted to subsequent layers through dense skip connections, as part of input of subsequent layers. This structure can fully multiplex features of different stages and different scales, and is capable of achieving better performance with less parameters and lower calculation costs than traditional residual network (ResNet). Tong et al. introduce dense neural network into image SR field and propose SRDenseNet (SR Dense Network)\cite{19}, which achieves considerable results.

In order to address the issue that medical images would suffer from severe blurring caused by lack of high-frequency details, inspired by the impressive performance of generative adversarial network, this paper develops a novel image SR algorithm called SR-DBAN via dense neural network and blended attention mechanism and a novel image SR algorithm via dense blended attention generative adversarial network called SR-DBAGAN. Our main contributions can be summarized as follows:

1. Firstly, we propose a novel blended attention mechanism block. The proposed attention block learns corresponding descriptor of each input feature map, multiplies the learned descriptor using Hadamard product with the original input, and simultaneously assigns different weights to different channels and different regions to enhance the channels and regions with sufficient high-frequency details and to suppress the channels and regions with abundant low-frequency texture contents. The proposed attention block is capable of enhancing feature representation capabilities, allowing the network to simultaneously focus on channels and regions that are with sufficient high-frequency details. Compared with phased attention design, the proposed block has fewer network parameters and gains higher efficiency.

2. Secondly, we propose a novel image SR algorithm called SR-DBAN via dense neural network and blended attention mechanism. The basic network structure is based on dense neural network, dense skip connections are added between the basic unit of the network and inside each basic unit, with which can fully multiplex features of different stages and different scales. At the end of each basic unit, the proposed blended attention mechanism block is added, so that the neural network can concentrate more attention on the channels and regions with sufficient high-frequency details, which can further improve the performance. Batch normalization layers in original DenseNet are removed to avoid loss of high-frequency texture details and final HR images are obtained through deconvolutional layers at the very end of the network.

3. Thirdly, we propose a novel image SR algorithm called SR-DBAGAN via dense blended attention generative adversarial network. SR-DBAGAN consists a generator and a discriminator, the generator uses our proposed SR-DBAN to generate HR images and try to fool the discriminator while the discriminator is designed based on Wasserstein GAN (WGAN) to discriminate whether the input is a real HR image or a generated SR image. We use the L1-Charbonnier\cite{20} loss function and the GAN loss to guide training, further enhancing the sharpness of generated HR images.

4. Last but not least, we deployed our algorithms on blurry prostate MRI images, and experimental results show that our proposed algorithms have generated considerable sharpness and texture details and have a significant improvement on the peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM), respectively, compared with the mainstream interpolation-based and deep learning-based image SR algorithms, which fully proves the effectiveness and superiority of our proposed algorithms. In addition to applying to MRI images, our proposed algorithms can also be applied to X-ray computed tomography (CT) images, X-ray (X-ray) images, and positron emission computed tomography (PET) images SR through transferring network structures, indicating favorable universality of our proposed algorithms.
2. Related theory

2.1. Dense neural network

The basic structure of primitive dense neural network is shown in Figure 1[18].

![Fig.1 Basic structure of primitive dense neural network](image)

The dense neural network is characterized by adding densely connected skip connections, fully multiplex features of different stages and different scales, and is capable of achieving better performance with less parameters and lower calculation costs than traditional residual network (ResNet). Besides, the dense skip connections allow the gradient information to be directly transmitted to any layer of the network during back propagation, greatly alleviating gradient vanishing and network degradation problems.

The essential difference between DenseNet and ResNet is that the input of any layer in DenseNet is derived from the output of all previous layers. Assuming the DenseNet has \(L\) layers, the output of \(l_{th}\) layer of DenseNet \(x_l\) is:

\[
x_l = H_l(\text{concat}(x_0, x_1, x_2 \cdots x_{l-1})), x_0, x_1, x_2 \cdots x_{l-1}, x_l \in \mathbb{R}^{H \times W \times C}
\]

where \(\text{concat}\) is the concatenation operation on the channel dimension. Equation 1 indicates that, the input of \(l_{th}\) layer is derived not only from the output of \((l-1)_{th}\) layer, but also from the output of all previous layers. Concatenate \(x_0, x_1, x_2 \cdots x_{l-1}\) in channel dimension, and take the concatenated feature maps as input of \(l_{th}\) nonlinear transforming operator \(H_l\). However, the output of \(l_{th}\) layer of ResNet is:

\[
x_l = H_l(x_{l-1}) + x_{l-1}, x_{l-1}, x_l \in \mathbb{R}^{H \times W \times C}
\]

Namely, the output of \(l_{th}\) layer is only the pixel-wise sum of the output of \((l-1)_{th}\) layer and the nonlinear transformation of the output of \((l-1)_{th}\) layer.

In view of the fact that DenseNet is capable of fully multiplexing features of different stages and different scales, and achieving better performance with less parameters and lower calculation costs than traditional residual network (ResNet), our proposed algorithms in this paper are based on dense neural network.

2.2. Attention mechanism

Attention mechanism refers to that neural networks are capable of focusing on specific channels or regions. According to the differences of concerns, attention mechanism can be divided into spatial attention mechanism and channel attention mechanism[21]. The cascaded channel-space attention mechanism proposed by Chen et al. [22] cascades the channel attention block and the spatial attention block together, and learns corresponding descriptors for different channels and different regions in stages, assigning different channels and different regions different weights, forcing the neural network concentrate more attention on the channels and regions with sufficient high-frequency details. Another channel attention structure proposed by Hu et al. [23] can adaptively assign different weights to different channels, enhance the channels with abundant high-frequency details, and suppress the channels with plentiful redundant low-frequency texture contents. The structure is capable of accelerating network convergence and further improves network performance.
2.3. Wasserstein GAN

Generative adversarial network (GAN) [24] first proposed by Goodfellow et al. in 2014 is the latest and most successful technology in generative model area. The main idea of GAN is to set up a zero-sum game with two participants. GAN consists a generator and a discriminator, the goal of generator is trying to fool the discriminator while the goal of discriminator is to discriminate whether the input obeys real data distribution or generated data distribution. The main weakness of the original GAN are the non-convergence problem and the model collapse problem [25]. Unlike traditional convex optimization problems with explicit objective functions, GAN’s optimization goal is to find a Nash equilibrium point. However, there is no theoretical analysis proving that GAN can always reach a Nash equilibrium point at present. In practice, loss oscillations often occur, which means that models tangled in what patterns to generate, and some equilibrium cannot be achieved. Model collapse, also called the Helvetica scenario means that GAN maps several different inputs to the same output. For example, the generator generates multiple images containing same colors and textures. Martin et al. pointed out that the loss function of the generator of original GAN is equivalent to Jensen-Shannon (JS) divergence between the real data distribution and the generated sample distribution assuming the discriminator is optimal. However, when the two distributions have no overlapping parts at all or their overlapping parts are negligible, the JS divergence of the two distributions is a constant, leading the gradients to zero, further leading to gradient vanishing. Martin et al. then propose to limit the sample distribution, assuming that the sample distribution obeys Lipschitz continuation, and uses the Wasserstein-1 distance to measure the difference between the real data distribution and the generated sample distribution. Based on that, Martin et al. propose Wasserstein GAN [25] whose convergence capability is much stronger than original GAN, and is one of the best-performing and widely used GAN variants.

The topology of Wasserstein GAN (WGAN) is shown in Figure 2, where \( z \) represents random noise, \( G \) represents generator, \( G(z) \) represents samples generated by generator, \( C \) represents discriminator, \( C(\cdot) \) represents approximate expression of Wasserstein-1 distance.

**Fig.2 Schematic of WGAN architecture**

WGAN uses Wasserstein-1 distance to measure the similarity between real data distribution and generated data distribution, and the definition is shown in Equation 3.

\[
W(P_r, P_g) = \inf_{\gamma \sim \Pi(P_r, P_g)} E_{(x, \tilde{x})}[||x - \tilde{x}||]
\]

where \( E_{(x, \tilde{x})}[||x - \tilde{x}||] \) is the ‘consumption’ of transforming generated data distribution to real data distribution when obeying the joint distribution \( \gamma \) of real data distribution and generated data distribution. \( W(P_r, P_g) \) is the minimum of the aforementioned ‘consumption’. Since the Wasserstein-1 distance cannot be solved directly, according to the Kantorovich-Rubinstein duality, the Wasserstein-1 distance can be approximated to find a continuous function \( f \) that satisfies the Lipschitz continuous condition. \( W(P_r, P_g) \) can be rewritten as Equation 4.

\[
W(P_r, P_g) = \frac{1}{K} \sup_{\|f\|_K \leq K} \mathbb{E}_{x \sim P_r}[f(x)] - \mathbb{E}_{x \sim P_g}[f(x)]
\]

In order to ensure \( f \) satisfies the Lipschitz continuous condition, weight clipping can be utilized and \( f(\cdot) \) can be fitted.
through a neural network. The goal of WGAN can be rewritten as a minimax problem shown as Equation 5.

$$\min G \max C \mathbb{E}_{x \sim P_r}[C(x)] - \mathbb{E}_{\tilde{x} \sim P_g}[C(\tilde{x})]$$ (5)

where $C(\bullet)$ represents approximate expression of Wasserstein-1 distance.

3. Proposed algorithms

3.1. Proposed blended attention mechanism

Adding a blended attention mechanism block in the network forces the neural network to concentrate more attention on the channels and regions with sufficient high-frequency details, which is capable of further improving performance. The proposed attention block cascades two convolutional and two activation layers, simultaneously learns corresponding descriptors for different channels and different regions, and assigns different channels and different regions different weights.

![Proposed blended attention mechanism block](image)

The proposed blended attention mechanism block is shown in Figure 3. The dimensions of the input and output feature maps are both $H \times W \times C$, $CONV$ represents convolutional operations, $RELU$ and $Sigmoid$ are two different activation functions[26], symbol $\otimes$ is Hadamard product[27]. Taking feature maps with dimensions $H \times W \times C$ as input, after two cascaded convolutions and activations as the figure 3 shows, corresponding descriptors $\tau$ will be obtained:

$$\tau = f(W_2\delta(W_1x)), \tau \in R^{H \times W \times C}$$ (6)

where $W_1, W_2$ represent the parameters of the first and the second convolutional layer, respectively. $\delta$ represents $RELU$ activation function while $f$ represents $Sigmoid$ activation function. The first convolutional layer performs channel down-scaling with reduction ratio 16, after that, feature maps with dimensions $H \times W \times C/16$ can be obtained. The obtained feature maps are then increased by ratio 16. After dimensions down-scaling and up-scaling by two cascaded convolutional layers and two activation layers, $C$ corresponding descriptive matrices namely descriptors $\tau$ for different channels where $i = 0, 1, 2...C$ are learned. Sparser descriptive matrices are adaptively assigned to channels that contain more low-frequency texture contents, this enables the neural network concentrate more attention on the channels and regions with sufficient high-frequency details. The dimension of each descriptive matrix $\tau_i$ is $H \times W$, corresponding to each element in $i_{th}$ channel of the original input. After two convolutions and two activations, the channels with abundant high-frequency details are enhanced, and the channels with plentiful redundant low-frequency texture contents are suppressed. Multiply the learned descriptor $\tau_i$ using hadamard product with the $i_{th}$ channel to force the network focus on the regions with sufficient high-frequency details in the $i_{th}$ channel. In summary, feature representation through blended attention mechanism block can be obtained by multiplying the learned descriptor $\tau$ and the original input.
The basic unit of the proposed dense blended attention network in this paper is shown in Figure 4a, where C represents channel concatenating, RELU and Sigmoid are two different activation functions. Each basic unit consists of eight cascaded convolutional layers, activation layers, and proposed blended attention blocks. Densely connected skip connections are added inside each basic unit, with which can fully multiplex features from different stages and different scales. Specifically, eight convolutional and activation operations are performed on the feature maps. The size of each convolution kernel is set to $16 \times 3 \times 3$, namely 16 kernels whose size is $3 \times 3$. Convolutional step size is set to 1, zero padding is used to keep the size of feature maps same\[28\]. Features from different stages and different scales are multiplexed due to dense skip connections. The number of channels of the convolution kernel increases linearly as the network deepens. In each basic unit, the number of channels of the first convolutional kernel is set to 16, and the number increases in each subsequent layer by 16 than the previous layer. After eight cascaded convolutions and activations, the feature maps are fed into the proposed blended attention block, and then output to the subsequent basic unit of the dense neural network to extract deeper features representations.

The overall schematic of the network is shown in Figure 4b, where Bottleneck represents the bottleneck layer[16]. Deconv represents the deconvolutional layer[15]. RELU, PRELU are two different activation functions. The whole network can be divided into three parts, namely feature extraction, nonlinear mapping, and reconstruction. The feature extraction part consists of concatenated convolution and activation layers. The convolutional kernel size is set to $128 \times 3 \times 3 \times 3$, that is, 128 convolution kernels with a size of $3 \times 3$, and the number of channels per kernel is 3. The nonlinear mapping part consists of eight cascaded basic units. Dense skip connections are added between the basic unit of the network, fully multiplexing features of different stages and different scales, greatly alleviating the problems of gradient vanishing and network degradation. The outputs of the eight basic units are concatenated together, and then fed into the subsequent
**Bottleneck** layer to perform channel-downscaling to reduce network parameters. After that, the final output HR images are amplified by the cascaded deconvolution layers and activation layers.

### 3.3. Adversarial network structure

The network structure of the WGAN-based discriminator proposed in this paper is shown in Figure 5 where *LeakyRELU* is a activation function, *Negative slope* is set to 0.2, *Batchnorm2d* is batch-normalized operation which normalize each batch input data, forcing them obey standard normal distribution, *Linear* is a linear regression function. The images input into discriminator are firstly fed into eight cascaded eight convolution, batch-normalization and activation layers to extract deep features representations, after that, they are fed into cascaded linear regression and activation layers to measure Wasserstein-1 distance between real data distribution and generated data distribution.

![Fig.5 Proposed adversarial network structure based on WGAN](image)

### 3.4. Loss function

Inspired by literature[20], we use the L1-Charbonnier loss function and the GAN loss of generator to quantify the similarity between the HR images obtained by deploying our SR algorithms and their HR counterparts, and guide training. The L1-Charbonnier loss function is shown as equation 7:

\[
L^{1-Charbonnier} - \text{Loss} = \frac{1}{n \times H \times W \times C} \sum_{v=1}^{n} \sum_{i}^{H} \sum_{j}^{W} \sum_{k}^{C} \rho(I_{v,i,j,k}^{HR} - I_{v,i,j,k}^{SR}) \tag{7}
\]

where \( \rho(x) = \sqrt{x^2 + \varepsilon^2} \), \( \varepsilon \) is set to \( 10^{-6} \), \( I^{HR} \) represents real HR images, \( I^{SR} \) represents HR images obtained by deploying our algorithms, \( H, W, C \) are spatial sizes and channel number of the input image respectively, \( n \) is number of mini-batch, \( I_{v,i,j,k} \) is the pixel value of position \((i, j)\) in the \( k \)th channel of the \( v \)th input image. The WGAN loss of generator is shown as equation 8:

\[
L^{WGAN}_G = -E_{x \sim p_g}[D_{WGAN}(x)] = \sum_{v=1}^{n} -D_{WGAN}(I^{SR}) \tag{8}
\]

where \( D_{WGAN} \) represents discriminator, \( x \sim p_g \) means that sample \( x \) obeys generated data distribution. The WGAN loss of discriminator is shown as equation 9:

\[
L^{WGAN}_D = -E_{x \sim p_r}[D_{WGAN}(x)] + E_{x \sim p_g}[D_{WGAN}(x)] = \sum_{v=1}^{n} -D_{WGAN}(I^{HR}) + \sum_{v=1}^{n} D_{WGAN}(I^{SR}) \tag{9}
\]

where \( x \sim p_r \) means that sample \( x \) obeys real data distribution. Thus, the total loss of generator consists of two weighted parts as shown in equation 10:

\[
L_G = L^{1-Charbonnier} - \text{Loss} + \lambda L^{WGAN}_G \tag{10}
\]

where \( \lambda \) is the balance factor to balance the L1-Charbonnier loss and the WGAN loss of generator, we empirically set \( \lambda \) to \( 10^{-4} \). The goal of the network in the training phase is to minimize the loss function \( L_G \). The smaller the \( L_G \) loss, the smaller the difference between obtained HR images and real HR images, the better the SR performance.
4. Experiment results and discussion

4.1. Datasets and training details

Training images used in this paper were prostate MRI public datasets of the University of Medicine, Nijmegen, Netherlands, which contains T2W, PD-W, DCE and DW images, all of which were derived from two different Siemens 3T MR scanners, the MAGNETOM Trio and Skyra[29]. T2-weighted images were acquired using a turbo spin echo sequence and had a resolution of around 0.5 mm in plane and a slice thickness of 3.6 mm. 400 T2W HR prostate MRI images with sufficient details whose size was 384 × 384 are selected as training set, and 100 T2W prostate MRI images were selected as testing set.

Training HR images are cropped to sub-images of size 96 × 96 as preprocessing procedure. LR images with scaling ratio 2, 3 and 4 are obtained by down-sampling HR images using the MATLAB imresize function. Data augmentation is performed on the training images, which are randomly rotated by 90°, 180°, 270° and flipped horizontally to obtain more training data. The mini-batch size is set to 16. For optimization, our proposed algorithms is optimized by ADAM optimizer with $\beta_1=0.9$, $\beta_2=0.999$, and $\epsilon=10^{-8}$[30]. The initial learning rate is set to $10^{-4}$ and then decreases to half after $3 \times 10^6$ iterations to achieve optimal results.

Two traditional SR algorithms and five representative deep learning-based algorithms were selected as comparative experiments. The traditional algorithms selected were bilinear interpolation(Bilinear) and bicubic interpolation(Bicubic). The selected deep learning algorithms were SRCNN[12], VDSR[13], FSRCNN[15], SRResNet[17] and SRDenseNet[19]. For fair comparison, we reproduced the comparative algorithms using their released codes under same hardware circumstances.

4.2. Evaluation standards

The metrics widely used to evaluate the image SR performance are peak signal-to-noise ratio(PSNR)[31] and structural similarity index(SSIM)[32]. PSNR and SSIM were chosen for quantitative evaluation in this paper. In addition, the real-time performance is also a vital indicator. Time required to complete single image SR is also used as one quantitative evaluation metric. For evaluation, inspired by the literature[33], this paper converted images from RGB color space to YCbCr color space[34]. All the metric results reported in this paper were computed on the luminance channel after removing scale number pixels border. The formula for calculating PSNR is:

$$PSNR = 10 \times \log_{10} \frac{255^2}{\frac{1}{W\times H} \sum_{i=1}^{W} \sum_{j=1}^{H} (I_{i,j}^{HR} - I_{i,j}^{SR})^2}$$  \hspace{1cm} (11)$$

where $W, H$ represents the image size, $I^{HR}$ represents real HR images, $I^{SR}$ represents the HR images obtained by SR, $I_{i,j}$ represents the pixel value of position $(i, j)$. The better the PSNR results, the better the image quality. The formula for calculating SSIM is:

$$SSIM(x, y) = \frac{2u_x u_y + C_1}{u_x^2 + u_y^2 + C_1} \times \frac{2\sigma_x \sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \times \frac{\sigma_{xy} + C_3}{\sigma_x \sigma_y + C_3}$$  \hspace{1cm} (12)$$

where $u, \sigma$ represents the pixel mean and variance of two images for comparison, $C_1, C_2, C_3$ represents the constants to prevent the denominator from being zero. The range of SSIM is $[0, 1]$, the closer the value is to 1, the more similar the two images.

4.3. Quantitative evaluation and discussion

The PSNR, SSIM, and time-consuming metric results obtained by SR of the testing set were averaged. The results are shown in Table 1.
Table 1. Quantitative evaluation results of each algorithm

| Algorithm | Scaling ratio: 2 |                      | Scaling ratio: 3 |                      | Scaling ratio: 4 |                      |
|-----------|-----------------|---------------------|-----------------|---------------------|-----------------|---------------------|
|           | PSNR/dB         | SSIM                | TIME/s          | PSNR/dB             | SSIM            | TIME/s             | PSNR/dB            | SSIM            | TIME/s |
| Bilinear  | 24.457          | 0.79361             | 0.0357          | 23.5452             | 0.71903         | 0.0344             | 22.6134           | 0.63552         | 0.0325 |
| Bicubic   | 25.5926         | 0.85839             | 0.0392          | 24.0203             | 0.75901         | 0.0365             | 23.1547           | 0.68166         | 0.0359 |
| SRCNN     | 30.1813         | 0.90659             | 0.3134          | 24.617              | 0.81318         | 0.3039             | 23.462            | 0.73439         | 0.318  |
| FSRCNN    | 30.1212         | 0.91186             | 0.3313          | 26.2499             | 0.82103         | 0.337              | 24.2736           | 0.73982         | 0.3091 |
| VDSR      | 34.7425         | 0.93066             | 0.3226          | 28.0425             | 0.82466         | 0.3496             | 24.1305           | 0.77406         | 0.3454 |
| SRResNet  | 35.0647         | 0.93172             | 0.3893          | 31.0468             | 0.86065         | 0.3712             | 29.116            | 0.80235         | 0.3766 |
| SRDenseNet| 35.5079         | 0.93337             | 0.4476          | 31.869              | 0.86593         | 0.4364             | 29.92             | 0.80955         | 0.4508 |
| **SR-DBAN** | **35.7043**    | **0.93397**         | **0.4623**      | **31.9154**         | **0.86704**     | **0.4684**         | **29.9721**       | **0.81085**     | **0.4701** |
| **SR-DBAGAN** | **35.7173**    | **0.9344**          | **0.4827**      | **31.9745**         | **0.86793**     | **0.4845**         | **30.0155**       | **0.81259**     | **0.4780** |

Clearly from Table 1 that our proposed algorithms SR-DBAN and SR-DBAGAN have a significant improvement on PSNR and SSIM, respectively, compared with the comparative interpolation-based and deep learning-based image SR algorithms.

Taking the quantitative evaluation results of scaling ratio 2 as an example, SR-DBAN has a significant improvement of 10.1117dB to 11.2473dB and 7.558% to 14.036%, while SR-DBAGAN has a significant improvement of 10.1247dB to 11.2603dB and 7.601% to 14.079% improvement on PSNR and SSIM, compared with the Bilinear and the Bicubic algorithms, respectively. Moreover, our proposed algorithms are also significantly improved compared with comparative deep learning-based algorithms. SR-DBAN exceeds comparative deep learning-based algorithms by PSNR and SSIM gains of 0.1964dB to 5.523dB and 0.06% to 2.738%, respectively. SR-DBAGAN exceeds comparative deep learning-based algorithms by PSNR and SSIM gains of 0.2094dB to 5.536dB and 0.103% to 2.781%, respectively. When it comes to time-consuming, bilinear algorithm was the fastest, time consumption of rest algorithms were higher than that, however, they are all within 0.5s which have favorable real-time performance.

It can be concluded from the quantitative evaluation results of scaling ratio 2, 3, 4 that performance of our proposed algorithms were superior to comparative algorithms. Combining the performance of each algorithm of different scaling ratio, the conclusion that our proposed algorithms were effective and superior can be drawn.

4.4. Qualitative evaluation and discussion

Four sets of images with sufficient texture details were selected from the testing set to show the performance of each algorithm with scaling ratio 2. The comparisons between HR images obtained by each algorithm and real HR images (Ground Truth, GT) are shown in Figure 6, and the corresponding quantitative evaluation results are marked below.

In overall, the images obtained by deep learning-based algorithms are clearer than that obtained by interpolation-based algorithms. SRCNN, FSRCNN, VDSR, SRResNet, SRDenseNet and our proposed algorithms in this paper achieved considerable performance, however, it can be noticed that more realistic texture details were produced by our proposed algorithms in specific areas. Taking the ProstateX-0061 image shown in Figure 6 as an example, the images obtained by bilinear and bicubic interpolation look blurry. The images obtained by SRCNN and FSRCNN have certain improvements compared with bicubic interpolation, however, they are still blurry and over-smoothed that appear implausible. VDSR, SRResNet, and SRDenseNet achieved favorable sharpness, but blurry artifacts appear. Images obtained by our proposed algorithms have gained better sharpness, uniform brightness, sufficient details and perception results, and are closest to
the real HR images.

4.5. Comprehensive evaluation and discussion

Combined with quantitative and qualitative evaluation results, the algorithms proposed in this paper have the characteristics of high precision. The quantitative results calculated by performing our proposed algorithms on the testing set are higher than that of traditional interpolation-based algorithms and the deep learning-based SRCNN, FSRCNN, VDSR, SRResNet and SRDenseNet algorithms. It can be noticed from the comparison of the rendering of each super resolution algorithm in Figure 6 that HR images obtained by our proposed algorithms have gained higher definition, better sharpness, uniform brightness, sufficient details and favorable perception results and are closest to the real HR images. When it to the time-consuming, our proposed algorithms improve performance with sacrifice of time, however, the consumed time is also within acceptable range.

In addition to applying to MRI images, our proposed algorithms can also be applied to X-ray computed tomography (CT) images, X-ray (X-ray) images, and positron emission computed tomography (PET) images SR through transferring network structures, indicating favorable universality of our proposed algorithms.

In summary, our proposed algorithms are superior than traditional interpolation-based algorithms and deep learning-based SRCNN, FSRCNN, VDSR, SRResNet and SRDenseNet algorithms.

5. Conclusion

In this paper, we proposed a novel blended attention block that is capable of enhancing feature representation capabilities, allowing the network to simultaneously focus on channels and regions with sufficient high-frequency details. Based on that, we proposed a novel image SR algorithm called SR-DBAN via dense neural network and the proposed blended attention mechanism. In addition, inspired by the impressive performance of generative adversarial network, we proposed a novel image SR algorithm called SR-DBAGAN via dense blended attention generative adversarial network. We deployed our algorithms on blurry prostate MRI images, and experimental results show that our proposed algorithms have generated considerable sharpness and texture details and have significant improvements on PSNR and SSIM, respectively, compared with the mainstream interpolation-based and deep learning-based image SR algorithms, which fully proves the effectiveness and superiority of our proposed algorithms.

Our proposed algorithms are of great significance for doctors to detect lesions more accurately and they are of great beneficial of improving the accuracy of clinical diagnosis. Furthermore, our proposed algorithms also provide a new idea for theoretical studies of medical images processing.

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Fig. 6 Comparison of qualitative results of each super resolution algorithm with scaling ratio 2
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