ISSN: 2472-3703 DOI: 10.6911/WSRJ.202305_9(5).0021

Self-supervised Image Denoising Algorithm Based on Improved Spatial Adaptive Network

Sheng Wang[1, 2], Hao Wu[1, 2], Zhongyang Jin[1, 2]

[1]School of Automation and Information Engineering, Sichuan University of Science and Engineering, Sichuan Zigong, 643000, China

[2]Key Laboratory of Artificial Intelligence in Sichuan Province, Sichuan Zigong, 643000, China

Abstract

An improved self supervised image denoising algorithm is proposed to solve the problems of blurring details and excessive artifacts in the image denoised by common denoising algorithms. This method combines the Neighbor2Neighbor self-monitoring training strategy with the spatial adaptive network SADNet, and uses the denoising network in the improved SADNet replacement training strategy to extract and process features. This method uses 7 × 7 size convolution layer extracts sufficient shallow feature information to improve the connectivity between feature mapping and codec structure, so as to enhance the network's ability to deal with different noise levels; Combined with single aggregation module and residual structure, intermediate feature extraction structure is designed to enhance feature aggregation to retain more detailed information; The RSAB structure is used to sample and weight the texture, detail and other features in the image, so as to restore the detail information and reduce the image artifacts. The experimental results show that the PSNR and SSIM values of the proposed algorithm are the highest compared with the common algorithms such as DnCNN, FDnCNN and FFDNet when tested on common BSD300, Kodak24, Set14, McMaster and Urban100 datasets; At the same time, the texture details of the denoised image are the clearest, the edge contour is obvious, and the visual effect is the best.

Keywords

Image denoising; Self-supervised learning; Spatial adaptive denoising network; Detail recovery; Residual structure.

1. INTRODUCTION

With the development of information technology, images have been widely used in military, medical, transportation and other fields, and are an important carrier for humans to obtain, process, and analyze external original information[1]. However, due to imperfect imaging systems and equipment, environmental and other factors[2], during the process of image acquisition, transmission, and storage, noise will inevitably occur. Noise will affect the integrity of image information extraction [3], and even cause humans to obtain incorrect information in severe cases. In order to better reflect the information carried by the original image, image denoising must be carried out.

Currently, image denoising methods are mainly divided into traditional denoising methods and depth learning based denoising methods [4]. Traditional methods are mainly divided into spatial domain denoising and transform domain denoising. Spatial domain denoising mainly uses filters to traverse every pixel in the image [5], mainly including mean filtering[6]and bilateral filtering [7]; Transform domain denoising converts an image from a spatial domain to

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a transform domain, adjusts the transform coefficients[8] to make the noise and image characteristics present different distributions in the transform domain, and finally performs an inverse transform to separate the two to achieve the purpose of denoising, mainly including Fourier transform [9] and wavelet transform [10]. Although the design of traditional denoising methods is simple, the amount of information extracted is limited. During the denoising process, it is easy to damage the details of the image, with obvious noise residues, and the model often does not have universality, limiting the development of practical applications.

With the development of computer software and hardware, deep learning based denoising methods have developed rapidly. Due to their powerful feature extraction capabilities and good denoising effects, they have gradually become the mainstream of image denoising methods. Currently, deep learning based denoising methods mainly include supervised denoising and self supervised denoising [11]. Supervised denoising is mainly performed by learning the difference between noise and clean images. In literature[12], a feedforward denoising convolutional neural network algorithm (DnCNN) was proposed in 2017, which uses residual learning and batch processing normalization to generate images containing only noise, and uses the original image to subtract the noise image to complete image denoising; The team also proposed a Fast and Flexible Denoising Network (FFDNet) algorithm by introducing a noise level map as input [13], enhancing the flexibility of the network against non-uniform noise; Literature [14]designed non local attention blocks to capture global information, but this method also brings high memory and time consumption. These depth denoisers require a large number of noise clean image pairs for training, but collecting a large number of training pairs is difficult, which greatly limits the use of supervised denoising algorithms. Therefore, some scholars propose to use self supervised methods for denoising. These methods utilize the independence between pixels to find the mapping relationship between the target pixel and the input pixel, thereby achieving the denoising task. Common methods include Noise2Noise [15], Noise2Void [16], and Noise2self [17]. However, the above self supervised denoising methods have problems such as inefficient network training, loss of useful information, or dependence on noise modeling.

Taking into account the shortcomings of existing methods, this paper proposes a self supervised image denoising algorithm that improves spatial adaptive networks. This method combines the self supervised training strategy Neighbor2Neighbor[18] and the spatial adaptive denoising network (SADNet) [19], aiming at directly using SADNet to replace the main network in the training strategy for feature extraction and processing, resulting in some image details blurring, artifacts, and other issues, Some improvements have been made to the network to reduce image artifacts while restoring detailed information. Finally, comparative experiments have been conducted on commonly used denoising datasets to verify the effectiveness of the denoising algorithm in this paper.

2. NEIGHBOR2BASIC PRINCIPLES OF NEIGHBOR SELF SUPERVISED NOISE REMOVAL

Neighbor2Neighbor is an extension of Noise2Noise, which indicates that a network trained using two independent noisy images in the same scene can represent the denoising network model in that scene, but it requires at least two independent noisy images in each scene, which is difficult to meet in real scenes; Therefore, Tao et al. [18]expanded two independent noisy images in the same scene into two independent noisy images in similar scenes: sampling adjacent areas of the original image using a neighbor sampler to obtain two independent sub images. The specific process is shown in Figure 1. From each single pixel, randomly select two neighboring pixels, namely Neighbors, to divide them into two sub images, and then fill them with red and blue, respectively, Using the pixels filled with red as the pixels of subsample image

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1 and the pixels filled with blue as the pixels of subsample image 2, two independent noisy images under similar scenes are obtained.

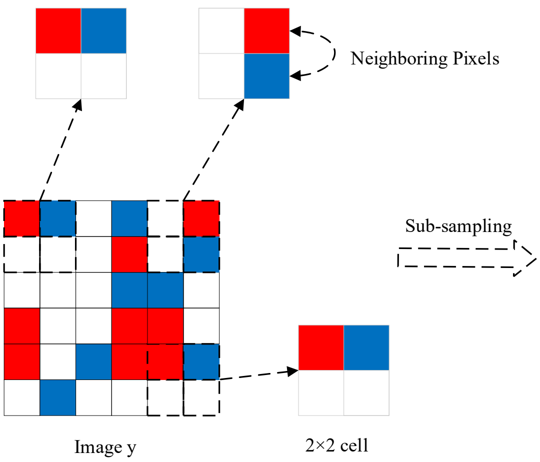

Figure 1. Schematic Diagram of Nearest Neighbor Sampling Strategy

After obtaining two independent noisy images in similar scenes using the nearest neighbor method, network training is conducted using the subgraph. The specific network training process is shown in Figure 2: After the noise image is inputted, a sub sampled image pair $(g_1(y), g_2(y))$ is obtained using the nearest neighbor sampler G, with $g_1(y)$ as the input of the network and $g_2(y)$ as the target; $g_1(y)$ obtains the denoised image $f_\theta(g_1(y))$ after passing through the network, and calculates the loss $L_{rec}=\left\|f_\theta\left(g_1(y)-g_2(y)\right)\right\|^2$ of the denoised image and the target; Obtaining a gradient free denoising image $f_\theta(y)$ after the noise image y passes through the network; And obtain a sampling pair $\left(g_1(f_\theta(y)), g_2(f_\theta(y))\right)$ using the same adjacent sub sampler G; Calculate the result of the regularization term, namely, $L_{reg}=\left\|f_\theta(g_1(y))-g_2(y)-g_1(f_\theta(y))+g_2(f_\theta(y))\right\|_2^2$; By minimizing the target $L_{rec}+\gamma L_{reg}$ and updating the denoising network in reverse, network training can be completed only through noisy images.

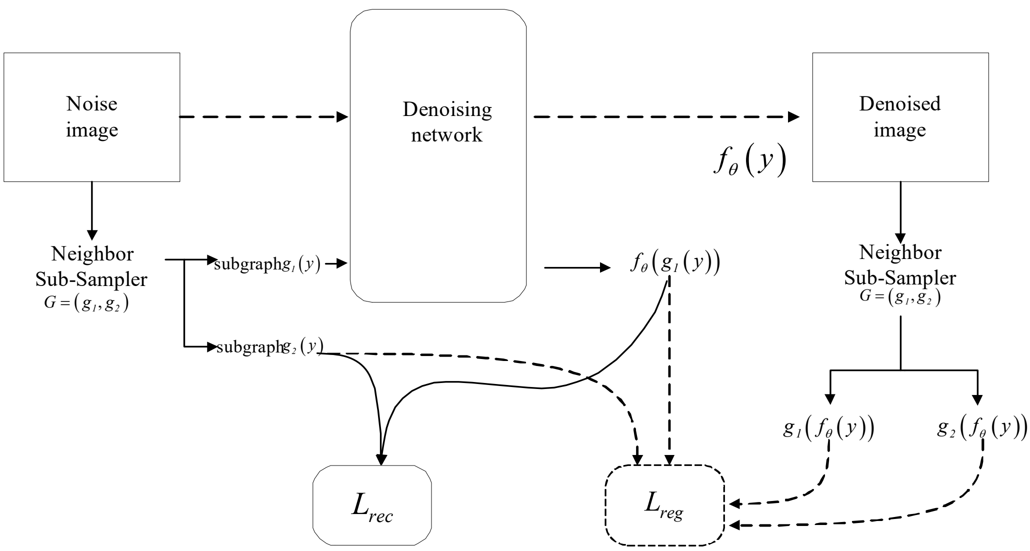

Figure 2. Neighbor2Neighbor Training Strategy

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3. SELF SUPERVISED NOISE REMOVAL ALGORITHM BASED ON IMPROVED SADNET

In Neighbor2Neighbor, U-Net is used as a denoising network to extract features. Due to the limitations of local rigid convolution operations [20], this method is prone to oversmooth artifacts and has limited denoising capabilities. Therefore, in order to further improve the network denoising performance, this article selects a network with better denoising capabilities and better detail recovery - SADNet; Some improvements have been made to the network, using the improved SADNet to replace the original U-Net, ensuring that the network removes noise while reducing the introduction of artifacts.

3.1. SADNet Network Architecture

SADNet was proposed by Zhang et al. in 2020. This network is mainly composed of Residual Spatial Adaptive Block (RSAB) and a codec structure. The former is used to adapt to changes in spatial texture and edges, while the latter is used to capture multiscale information, enabling the network to estimate offsets and remove noise from coarse to fine.

The RSAB module proposed by the network can change the sampling position based on the image content to extract relevant features: in smooth or uniform texture regions, the convolution kernel is approximately uniformly distributed, and in regions close to the edge, the shape of the convolution kernel extends along the edge, with most sampling points falling on similar texture regions within the object. The network introduces modulated deformable convolution into each RSAB, enabling the network to sample and weight relevant features based on the content and texture of the image. The overall structure is shown in Figure 3.

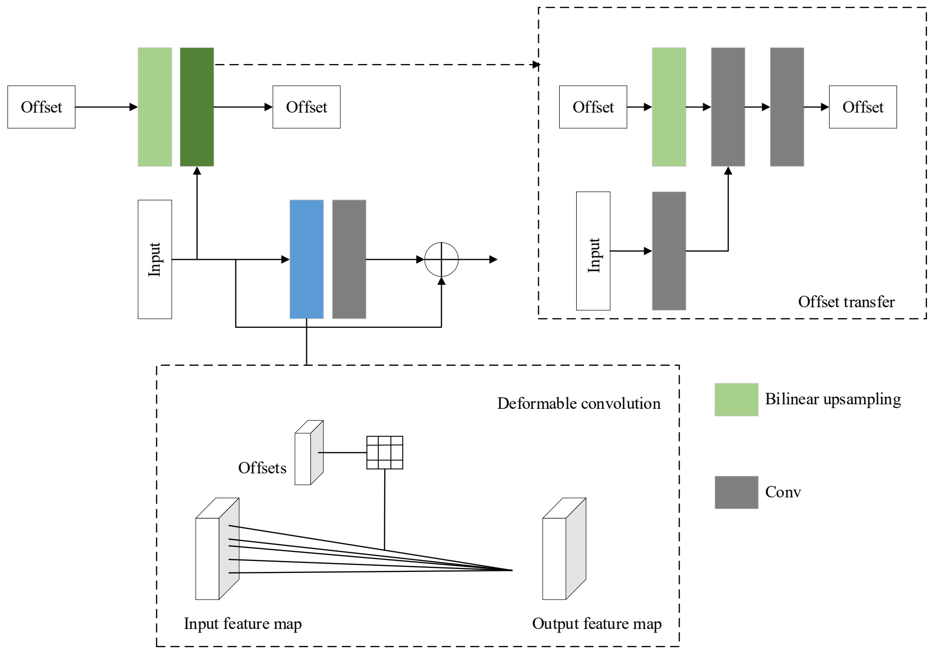

Figure 3. Structure of RSAB

Initial Utilization of SADNet Network used 1 × 1 size convolution layer is not sufficient to extract shallow features, and the ability of the network to handle different noise levels is insufficient. Direct application can easily lead to noise residues in the denoised image; In the network coding stage, residual structure is used to extract features. The input of the context module is only the output of the previous residual structure. The utilization of intermediate features is insufficient, and artifacts are prone to appear in the image. Therefore, it is necessary to improve the SADNet network.

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3.2. Improved SADNet Network

3.2.1 Shallow feature extraction

Image denoising is a low-level image processing task [21] [22], aimed at restoring clean and clear images from noisy images. This article utilizes 7 × 7 size convolution layer replaces original 1 × 1 size convolution layer extracts more comprehensive shallow image information to improve the connectivity between feature mapping and codec structures, thereby enhancing the ability of the network to handle different noise levels.

3.2.2 Fusion OSA feature aggregation structure

The input of the original network context module is only the output of the previous residual structure, and the utilization ability of intermediate features is insufficient. Therefore, in order to preserve intermediate features extracted by different residuals, it is necessary to add a jump connection structure. The most commonly used method is DenseNet [23]. Although traditional dense connections can achieve feature reuse through the connection of features on the channel, they also cause a linear increase in the input channel, resulting in excessive computational overhead and energy consumption. In 2019, Lee et al[24] proposed a single aggregation (OSA) module, which overcomes the inefficiency of dense connections while preserving the reuse of DenseNet multiple acceptance domain features by aggregating all features only once in the last feature map. Therefore, this article draws on OSA and residual structure to design a feature fusion structure and names it VOV-Residual. Its structure is shown in Figure 4.

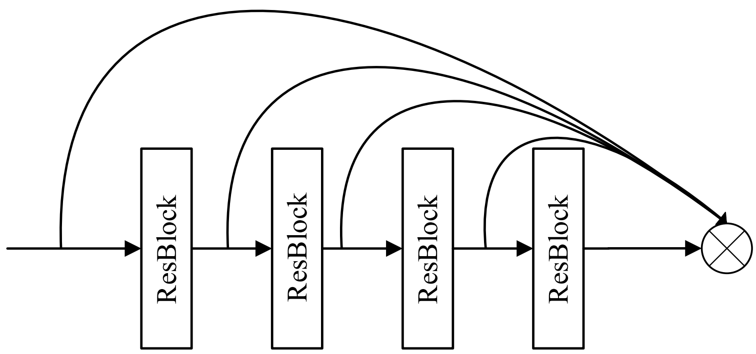

Figure 4. Structure diagram of VOV-Reactive

This structure sequentially extracts the feature information of the image through a four layer residual structure, enhances the information flow using local residual learning, improves the representation ability of the network, and aggregates the intermediate features extracted from each residual structure at the last layer, achieving feature information aggregation while reducing network resource consumption.

In order to extract more low-level information, 7 × 7 size convolution layer for feature extraction; In order to make full use of intermediate features, a feature fusion structure, VOV-Reactive, is designed to achieve the aggregation of feature information. The improved denoising network model is as follows.

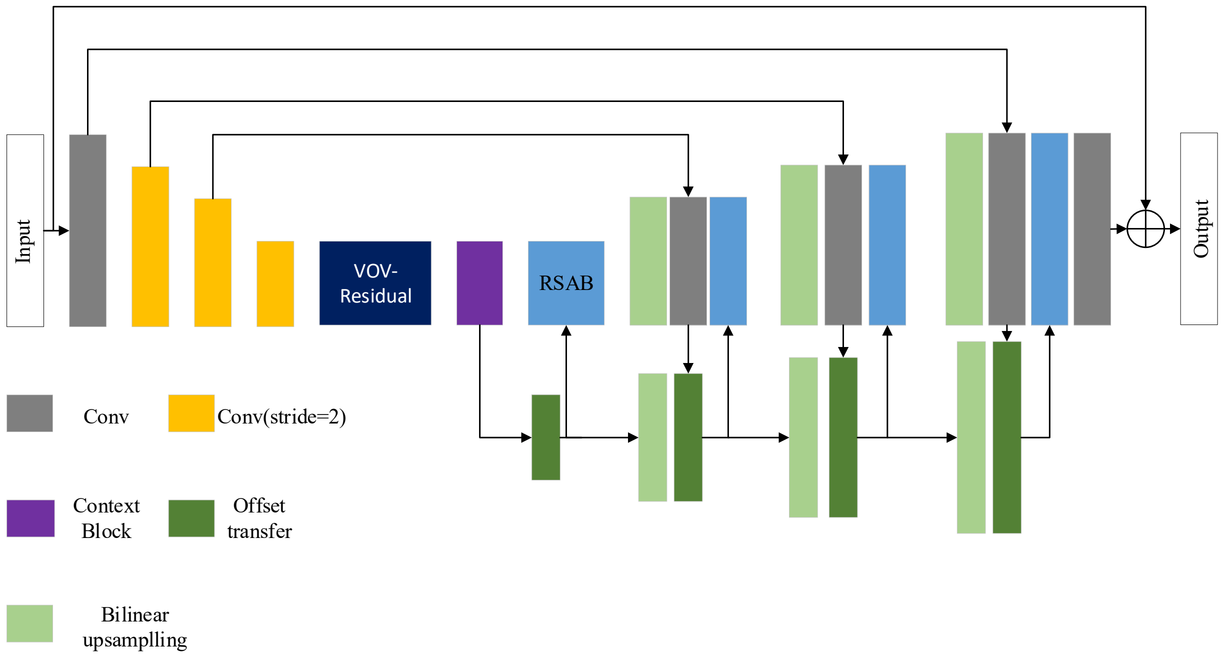

Figure 5. Improving the Network Structure of SADNet

The network first passes through 7 × 7 size convolution layer extracts shallow features from the input noise image; Then, the codec architecture performs deep feature extraction. In the encoder, the feature map first passes through three down sampling layers, and each down sampling module consists of two × A convolution kernel (with a step size of 2) and an activation function Leaky ReLU; Then input the image features extracted by integrating the residual structure into the feature aggregation structure of the fused OSA, and then input the integrated features into the context block to further expand the acceptance domain and capture multi-scale information; In the decoder, RSAB is used to sample and weight relevant features to remove noise and reconstruct texture, and bilinear interpolation is used to upsample offset and modulation scalar to reconstruct image features layer by layer; Finally, input the reconstructed features into the feature fusion layer, and use 1 × The convolution of 1 restores the size of the feature map to the size of the input image. In order to avoid information blocking, the output features and input features are connected through a jump connection to obtain the final denoised image.

4. EXPERIMENT AND RESULT ANALYSIS

4.1. Datasets and parameter settings

In this article, 44283 images from the ImageNet_ val dataset are used as training sets, and then images are randomly cropped to 256 × 256 patches for training, with a total training round set to 300, batch_ The size is 64, the model is saved once every two rounds of iteration, and an Adam optimizer is used with an initial learning rate of 0.0003. The denoising network is reversely updated using the loss of self supervised learning. Effects are tested on the common denoising data sets BSD300, Kodak24, Set14, McMaster, and Urban100.

The training and testing of the denoising algorithm in this article are conducted on the workstation, making full use of the accelerated processing of the GPU. The specific configuration is shown in Table 1.

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Table 1. Experimental Environment Parameters

Software/Hardware	model
OS	Windows 10 Professional Edition
CPU	AMD EPYC 7302
GPU	Nvidia Ampere A100
Deep Learning Framework	Pytorch
Python version	3.8

4.2. Evaluation index

This article selects the two most commonly used evaluation indicators in the field of image denoising: Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM) [25]for algorithm evaluation. The peak performance to noise ratio is proposed based on pixel statistics. It evaluates image quality by calculating pixel errors in a global range, expressed as the ratio of the maximum power of the signal to the noise power of the signal. The larger the value, the smaller the distortion between the denoised image and the original image, and the more noise is removed.

$$PSNR = 10\lg\frac{L^2}{MSE} \tag{1}$$

In the formula, L represents the maximum value of pixel points, and MSE represents the Mean Square Error (MSE), which reflects the difference between the denoised image and the original image. The calculation formula is as follows.

$$MSE = \frac{1}{N}\sum_{t=1}^{N}\left(x_i - y_i\right)^2 \tag{2}$$

x_i and y_i are the denoised and clean images, respectively; N being the number of pixel points.

SSIM focuses on the correlation between image pixels, using the mean value to estimate the brightness of the image, evaluating the contrast and structural information similarity using the standard deviation and covariance of the image. SSIM analyzes the approximate information of image distortion by comparing the differences in structural information of the image, and is able to perceive changes in low-level features such as edges and structures of the image. The value is between 0 and 1, and the larger the value, the higher the structural feature similarity of the two images, The better the noise removal effect.

$$\begin{cases} SSIM = \left[l(x,y)\right]^{\alpha}\left[c(x,y)\right]^{\beta}\left[s(x,y)\right]^{\gamma} \\ l(x,y) = \dfrac{2\mu_x\mu_y + C_1}{\mu_x^{\,2} + \mu_y^{\,2} + C_1} \\ c(x,y) = \dfrac{2\sigma_x\sigma_y + C_2}{\sigma_x^{\,2} + \sigma_y^{\,2} + C_2} \\ s(x,y) = \dfrac{2\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \end{cases} \tag{3}$$

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In the above formula, $l(x,y)$ represents image brightness, $c(x,y)$ represents contrast between images, and $s(x,y)$ represents structural information similarity of images; α, β and γ are the adjustment parameters for SSIM and are all greater than 0. μ_x, μ_y are the average values of the images, σ_x, σ_y represent the standard deviation between the two images, σ_{xy} is the covariance of the two images, and C_1, C_2 and C_3 are the denominator adjustment coefficients to prevent computational errors caused by a denominator of 0.

4.3. Results and Analysis

In order to verify the effectiveness of the denoising algorithm in this paper, algorithms such as DnCNN, FDnCNN, FFDNet, and Neighbor2Neighbor were selected for comparative experiments on a test set. The advantages and disadvantages of each algorithm under different noise levels were analyzed from both numerical and subjective aspects.

4.3.1 Objective assessment

To evaluate the advantages and disadvantages of each denoising algorithm under different noise levels, the PSNR and SSIM values of each denoising algorithm on the test set were calculated during the experiment. In order to better analyze the denoising ability of the proposed algorithm, Gaussian noise with noise levels of 25, 30, and 50 was used for effect testing, as shown in Table 2. It can be seen from the table that as the noise level increases, the denoising ability of each algorithm gradually decreases, which conforms to the change rule of the denoising model; Through quantitative experimental data analysis, it can be seen that the algorithm in this paper can achieve the highest PSNR and SSIM values in each dataset and at each noise level, indicating that the distortion between the image and the original image after denoising by the algorithm in this paper is minimal, and the correlation between image pixels is highest. From a numerical perspective, the denoising effect of the algorithm in this paper is the best.

Table 2. Comparison of image evaluation indicators

Datasets	Noise level	DnCNN	FDnCNN	FFDNet	Neighbor 2Neighbor	ours
BSD300	25	29.32/0.83	30.60/0.87	30.64/0.87	30.65/0.87	31.03/0.88
	30	28.67/0.80	29.73/0.84	29.81/0.85	29.89/0.85	30.20/0.86
	50	25.54/0.67	27.41/0.76	27.59/0.77	27.46/0.76	27.88/0.78
Kodak24	25	30.04/0.82	31.58/0.87	31.65/0.87	31.80/0.87	32.29/0.88
	30	29.45/0.80	30.76/0.85	30.87/0.85	31.10/0.86	31.25/0.87
	50	26.30/0.68	28.51/0.78	28.71/0.79	28.73/0.78	29.28/0.86
Set14	25	28.81/0.80	30.41/0.87	30.38/0.85	30.85/0.86	31.26/0.87
	30	28.21/0.79	29.71/0.83	29.74/0.84	30.18/0.84	30.56/0.85
	50	25.33/0.67	27.64/0.77	27.82/0.78	27.99/0.78	28.46/0.80
McMaster	25	29.67/0.82	31.41/0.87	31.51/0.87	32.04/0.88	32.50/0.89
	30	29.15/0.80	30.65/0.85	30.81/0.86	31.30/0.87	31.74/0.88
	50	25.97/0.68	28.45/0.80	28.75/0.81	28.90/0.81	29.47/0.83
Urban100	25	28.55/0.85	30.70/0.90	30.60/0.90	30.71/0.90	31.32/0.91
	30	27.81/0.83	29.86/0.89	29.83/0.89	30.02/0.89	30.57/0.90
	50	24.72/0.73	27.40/0.83	27.57/0.84	27.54/0.83	28.22/0.86

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3.3.2 Subjective evaluation

In order to more intuitively illustrate the effectiveness of the denoising algorithm in this article, this article selects the results of each test set with a noise level of 50 to display, and analyzes the overall denoising effect and the detailed restoration situation respectively.

(1)Overall noise removal effect

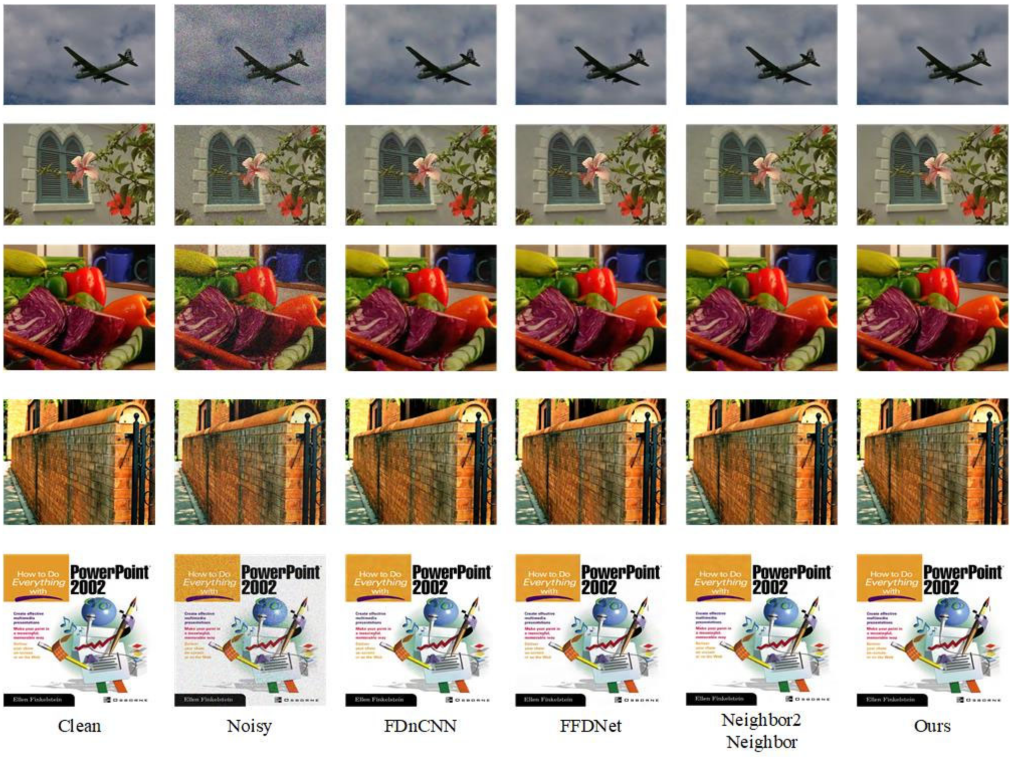

Figure 6. Overall Noise Removal Effect of Test Set

The overall denoising effect comparison between the experimental results of this algorithm and the comparison algorithm is shown in Figure 6. One image is selected from each of the five data sets to demonstrate the effect. As can be seen from Figure 6, there will be more noise residues in the image after FDnCNN denoising, resulting in serious loss of image information; Although FFDNet and Neighbor2Neighbor have further improved their noise removal capabilities, they are prone to create overly smooth artifacts when removing noise from walls and vegetable surfaces, without taking into account detailed information such as the surface texture of the image; The denoising algorithm in this paper can effectively restore the detailed information of the original image while removing noise, such as water droplets on vegetables, veins on petals, and signs on airplanes. The overall color rendering of the denoised image is also closer to the original image.

(2) Details recovery

In order to demonstrate the denoising effect of each algorithm in more detail, images from the BSD300, Kodak24, and Set14 datasets were selected, and two parts were taken from each image for detailed display and comparison. The effect is shown in Figure 7.

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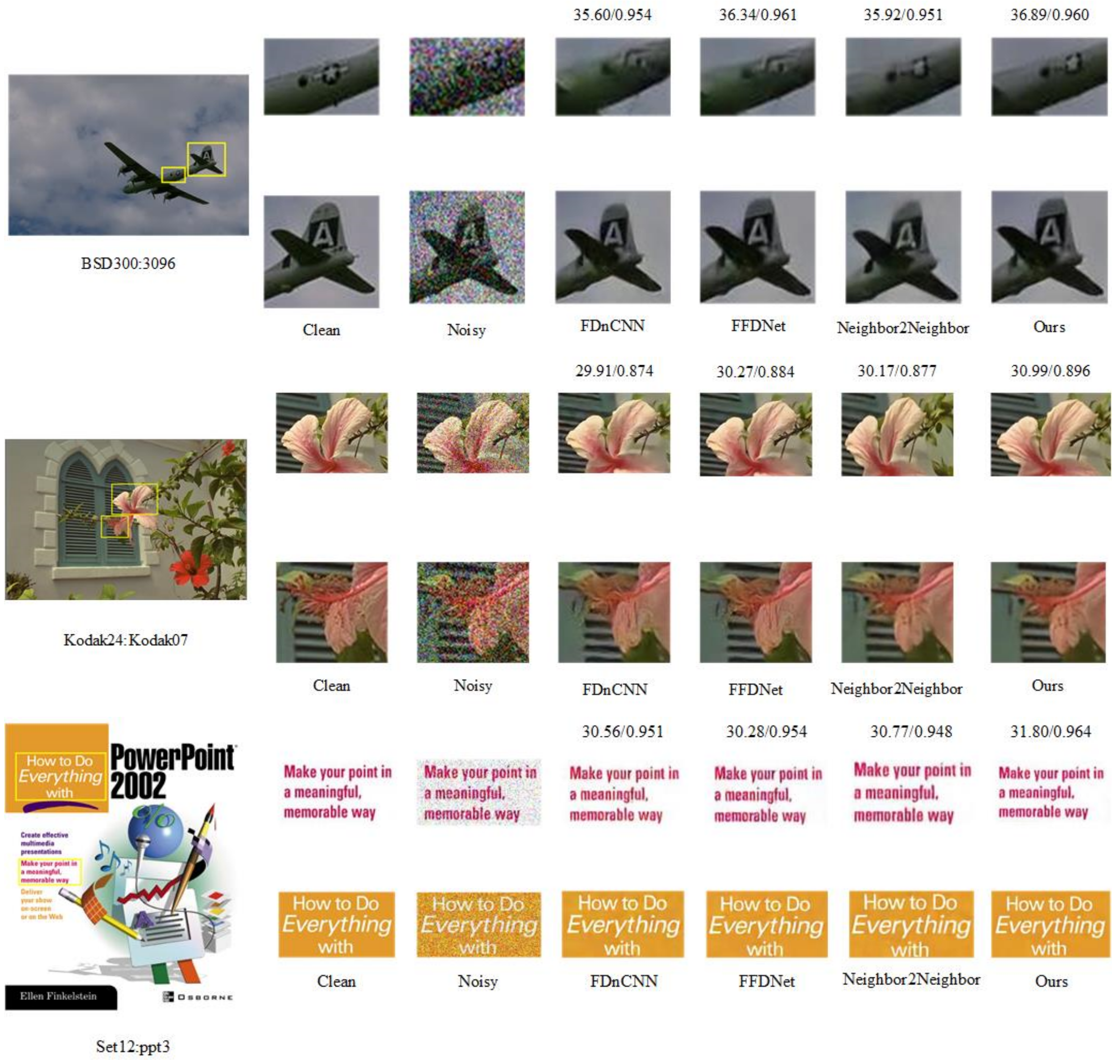

Figure 7. Detailed display of noise removal effect

The first image shows the denoising effect of each algorithm on the fuselage and tail of an aircraft. Only the algorithm in this article can better restore the fuselage pattern, while the other image denoised by the comparison algorithm can only roughly restore the shape of the fuselage, and the fuselage pattern is even more severely blurred; Secondly, at the tail, the detailed information at the tail after denoising by this algorithm is rich, and the overall image is clearer;

The second image shows the denoising effect of each algorithm on petals and stamens. The denoised petals surface texture details of this algorithm are more realistic, with clear edge contours and consistent with the actual situation; The contrast algorithm can only restore the petals, but the texture depiction of the petal surface is not clear enough, and there are still a large number of noise residues; In the case of flower stamen denoising, the algorithm in this paper can better restore the detailed information of the flower stamen, while maintaining the clarity of the image information around the flower stamen, and the depiction of the pane behind the flower stamen is also closer to the original image; The image denoised by the contrast algorithm appears blurred at the stamens, and the details of the stamens are severely damaged, only the blurred pane behind the stamens can be restored;

The third image shows the denoising effect of each algorithm on the letters in the image. Both the comparison algorithm and the algorithm in this article can recover the letter information, but the image denoised by the comparison method still has noise residues around the letters, and the edges of the letters are relatively fuzzy; After denoising by the algorithm in this paper, the edge details of the letters are closer to the original image, and the overall letter is clearer.

5. CONCLUSION

To alleviate the problems of blurred details and excessive artifacts in denoised images, this paper proposes a self supervised image denoising algorithm by combining Neighbor2Neighbor's self supervised training strategy with an improved SADNet. This method first utilizes 7 × The convolution kernel of 7 extracts sufficient shallow feature information; Secondly, design an intermediate feature extraction structure combining VOVNet and residual structure to achieve feature aggregation while reducing some resource consumption and retaining more detailed information; Finally, the RSAB structure is used to achieve the adaptability of image content, restoring more texture information while reducing image artifacts. After comparative experiments, compared to the comparison algorithm, the algorithm in this paper retains more image details while removing noise, and the image after denoising has clearer edges and more natural texture; The objective evaluation indicators PSNR and SSIM also indicate that the image denoised by this algorithm has the smallest distortion, the highest structural similarity, and the subjective visual perception is consistent with the objective evaluation analysis results, which has certain reference value. Although the algorithm in this paper has achieved good results on the test dataset, as the noise level increases, the network denoising performance decreases rapidly. In the future, we will continue to study image denoising under high noise to further improve the network denoising performance, in order to better recover the information carried by the original image.

ACKNOWLEDGMENTS

Fund projects: The Project of Sichuan provincial science and Technology Department (Grant No. 2020YFG0178, 2021YFG0313, 2022YFS0518, 2022ZHCG0035); The Project supported by the Graduate Innovation Fund of Sichuan University of Science and Engineering (y2021075); The artificial intelligence key laboratory of Sichuan province Foundation (2019RYY01).

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