A New Algorithm for High Dynamic Range Image Denoising based on Generative Adversarial Networks

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Abstract:

In this study, a new algorithm for high dynamic range image denoising based on generative adversarial network is successfully designed and implemented, and a series of innovative and practical research results are achieved in the field of image denoising. In terms of algorithm design, the structure of the generative adversarial network is innovatively optimised, which enhances the ability of retaining image details, judges the authenticity of the generated image more effectively, and improves the adversarial effect of the generative adversarial network. In terms of loss function design, a multi-loss function optimisation strategy that integrates the consideration of adversarial loss, content loss and structural loss is proposed to make the generated denoised image visually similar to the real noise-free image through the adversarial game between the generator and the discriminator, reasonably adjusting the weight of each loss term to achieve effective constraints on the generator and improve the quality of the denoised image. Compared with traditional denoising algorithms such as mean filtering, median filtering and Gaussian filtering, this algorithm has significant advantages in objective evaluation indexes such as peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM), which can remove noise more effectively while retaining the details and structural information of the image in a better way, and the visual effect of the denoised image is significantly improved. The denoising time of a single image in the testing stage is short, and the memory consumption is within the acceptable range, which can meet the needs of practical applications.

Keywords: generative adversarial networks; high dynamic range images; image denoising; multiple loss functions; objective evaluation metrics

1 Introduction

1.1 Background and significance of the study

In today's digital era, image technology plays a crucial role in many fields. As a type of image that can more accurately represent the range of brightness changes in a real scene, High Dynamic Range (HDR) images have unparalleled advantages over traditional Low Dynamic Range (LDR) images, and they occupy an increasingly important position in practical applications. In the field of film and television production, HDR images can present more realistic colors and lighting effects, bringing the audience an immersive visual experience [1]. In the field of medical imaging, HDR images can provide richer medical information and help doctors diagnose conditions more accurately. Take X-ray images as an example, HDR technology can make the details of bones, soft tissues and lesions present clearly at the same time, avoiding the loss of information due to the limitation of the brightness range, thus improving the accuracy of early diagnosis of diseases and gaining valuable time for patients' treatment. In industrial inspection, for the inspection of some precision parts, HDR images can clearly show the subtle defects and texture features on the surface, ensuring that product quality meets strict standards [2].

However, during the acquisition and transmission of HDR images, they are inevitably interfered by various noises. These noises come from a variety of sources, such as the electronic noise of the image sensor itself, electromagnetic interference in the shooting environment, signal attenuation during transmission, and so on. The presence of noise seriously affects the quality of HDR images, making the details in the image blurred and reducing the visual effect and application value of the image [3]. In the HDR image of night scene shooting, noise may make the original clear outline of the building become blurred, and the bright spots of the stars are covered by noise, which can not show the beautiful night sky scenery; in the medical HDR image, noise may interfere with the doctor's judgment of the lesion site, resulting in an increased risk of misdiagnosis or omission of diagnosis.

1.2 Current status of image denoising research

In the late 20th century, Dr. Paul Debevec of the University of Southern California (USC) publicly proposed the technique of combining multiple images of different exposures to produce HDR images. 1997, he presented a paper entitled "Recovering High Dynamic Range Glossy Images from Photographs" at SIGGRAPH, describing the method of compositing HDR images by taking multiple shots of the same image with different exposures, and combining and processing these images to obtain a composite HDR image. This combination of pre-shooting and post-processing dramatically improved image quality. Since then, various computer-applied algorithms, such as compression of bit depth, have been developed to enable HDR images to be displayed on conventional devices [4].

In order to overcome the effect of noise on HDR images and improve image quality, it is an urgent necessity to study efficient denoising algorithms. Traditional image denoising algorithms, such as mean filtering, median filtering, Gaussian filtering, etc., although to a certain extent able to remove the noise, but often at the expense of the details and edge information of the image, the effect is not ideal for HDR images, which are an image type that requires a high level of detail. With the rapid development of deep learning technology, image denoising algorithms based on deep learning have gradually become a research hotspot, in which Generative Adversarial Networks (GANs) have shown great potential in the field of image denoising due to their unique adversarial learning mechanism. In the quest to overcome the impact of noise on HDR images, it is urgent to improve image quality and develop efficient denoising algorithms [5]. Traditional image denoising algorithms, such as mean filtering, median filtering and Gaussian filtering, have indeed demonstrated the ability to remove noise to a certain extent in past research and applications. Early research pointed out that mean filtering replaces the center pixel by calculating the average value of neighboring pixels to achieve the purpose of smoothing the image and reducing the noise, but this simple averaging operation is very easy to blur the details of the image, especially when dealing with the edges and texture-rich regions with poor results. Median filtering, on the other hand, selects the median of the pixel values in the neighborhood to replace the center pixel, which has some advantages in removing impulse noises such as pretzel noise, but for images with complex textures and fine structures, it will also result in the loss of details [6].

In this field, Generative Adversarial Networks (GANs) have emerged with their unique adversarial learning mechanism, showing great potential for application. Previous research has initially applied GAN to image denoising, through the mutual game of generator and discriminator, the generator learns the mapping relationship to restore a clear image from a noisy image, and the discriminator is committed to distinguishing between the generated image and the real clear image, and the adversarial training of the two prompts the generator to continuously optimize in order to generate a denoised image that is closer to the real one. However, the existing GAN-based HDR image denoising research still has some problems, such as the generation of images prone to artifacts, the lack of adaptability to complex noise scenes, and so on, and urgently needs further in-depth research and improvement.

1.3 Content of the study

The aim of this study is to explore the new algorithm of high dynamic range image denoising based on generative adversarial network, and to improve the denoising effect of HDR images through innovative algorithm design and optimization, so that it can effectively remove the noise interference while retaining the rich details and high dynamic range information. This not only helps to promote the development of image denoising technology and provide new ideas and methods for the research in related fields, but also has important practical application value, which can provide high-quality HDR images for film and television production, medical imaging, industrial inspection and other fields, and promote the technological progress and development of these fields [7].

2 Materials and Experimental Methods

2.1 Generating Adversarial Network Grounded Theory

Generative Adversarial Networks are a highly innovative deep learning framework consisting of two mutually adversarial neural networks, the generator and the discriminator, and this adversarial learning mechanism allows GANs to show unique advantages in learning data distributions and generating realistic samples. The main responsibility of the generator is to take random noise as input, transform and process it through a series of neural network layers to generate samples similar to real data. The discriminator, on the other hand, is a binary classifier whose task is to determine whether the input sample is from the real dataset or generated by the generator. It receives the input sample and then extracts and analyzes the features of the sample through neural network layers such as convolutional, pooling, and fully connected layers, and then outputs a probability value indicating the likelihood that the sample is a real sample.

During the training process, the generator and the discriminator play an intense adversarial game. The generator tries to generate more realistic samples to deceive the discriminator, so that it misjudges the generated samples as real samples; while the discriminator tries to improve its discriminative ability to accurately recognize the samples generated by the generator. This confrontation process can be likened to a game of "cat and mouse", in which the generator and the discriminator continuously optimize their parameters to improve their performance.

2.2 Principles of Generative Adversarial Networks in Image Denoising

In the field of image denoising, generative adversarial network provides a brand new idea and method for solving the noise interference problem by virtue of its unique adversarial learning mechanism. Its core principle is to utilize the mutual collaboration and competition between the generator and the discriminator, so that the generator can learn the mapping relationship from the noisy image to the clear image, thus realizing the effective denoising of the noisy image [8].

During the training process, the generator and the discriminator confront and learn from each other. The generator strives to generate more realistic denoised images to deceive the discriminator so that it misjudges the generated denoised image as a real noiseless image; while the discriminator continuously improves its discriminative ability to accurately recognize the denoised image generated by the generator. This confrontation process prompts the generator to continuously optimize its own network parameters and learn a more effective denoising strategy, thus improving the quality of the denoised image. The specific training process is as follows: first, a batch of noisy images and corresponding real noisy images are selected from the training dataset. The noisy images are input into the generator, which generates the denoised images.

Fixing the parameters of the discriminator, the noisy image is again fed into the generator, which generates a new denoised image. At this point, the generator's goal is to minimize the probability that the discriminator will judge its generated denoised image as false, i.e., maximize the probability that the discriminator will judge its generated denoised image as true. Through the back-propagation algorithm, the parameters of the generator are updated according to the gradient computed from the generator's loss function (which is usually related to the discriminator's loss function) to make the denoised image it generates more realistic [9].

By continuously training the generator and discriminator alternately, the generator gradually learns the mapping relationship between the noisy image and the real noise-free image, and is able to generate high-quality denoised images. In the test phase, the noisy image to be denoised is input into the trained generator, and the generator can output a clear image after denoising, thus realizing the purpose of image denoising.

2.3 New Algorithm Design

2.3.1 Network architecture design

The network structure of the high dynamic range image denoising algorithm based on generative adversarial network designed in this paper is mainly composed of two parts: generator and discriminator, which collaborate with each other to realize the denoising of high dynamic range images by means of adversarial learning. Where the network model diagram is shown in Figure 1.

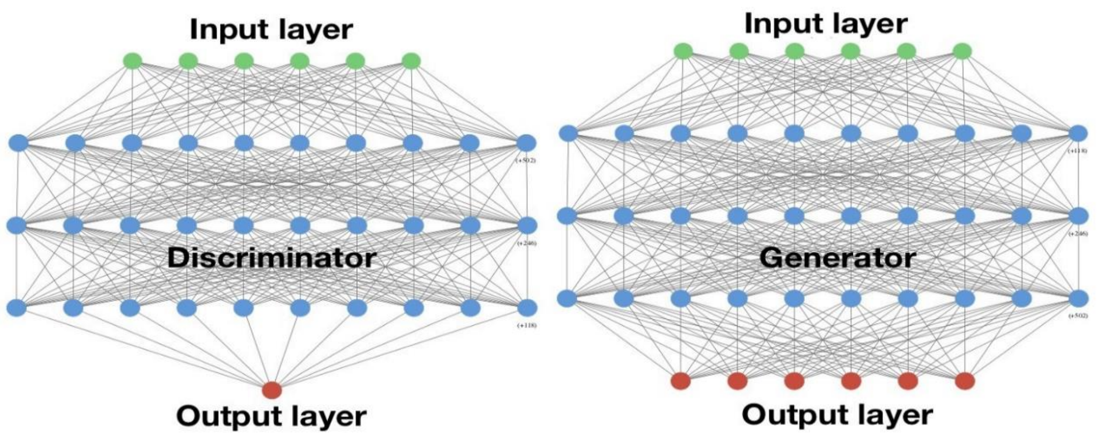

Fig. 1 Network model diagram

The input to the generator is a noisy image, which first undergoes a series of downsampling convolutional layers to gradually reduce the resolution of the image while increasing the number of channels of the feature map to extract the deeper features of the image. The downsampling convolutional layer consists of a convolutional layer, a batch normalization layer and a ReLU activation function, with a convolutional kernel size of 3×3, a step size of 2, and a padding of 1. After four downsamplings, the resolution of the image becomes 1/16 of the original one, and the number of channels of the feature map is increased to 256. Then, through a series of up-sampling inverse convolutional layers, the resolution of the image is gradually restored, and at the same time the number of channels of the feature map is reduced to map the extracted features back to the image space [10]. The extracted features are mapped back to the image space. The up-sampling inverse convolution layer also consists of an inverse convolution layer, a batch normalization layer and a ReLU activation function, and the size of the inverse convolution kernel is 4×4, the step size is 2, and the padding is 1. After 4 times of up-sampling, the resolution of the image is restored to the original size, and the number of channels of the feature map is reduced to 3, so that the de-noised image is obtained. The schematic is shown in Fig. 2.

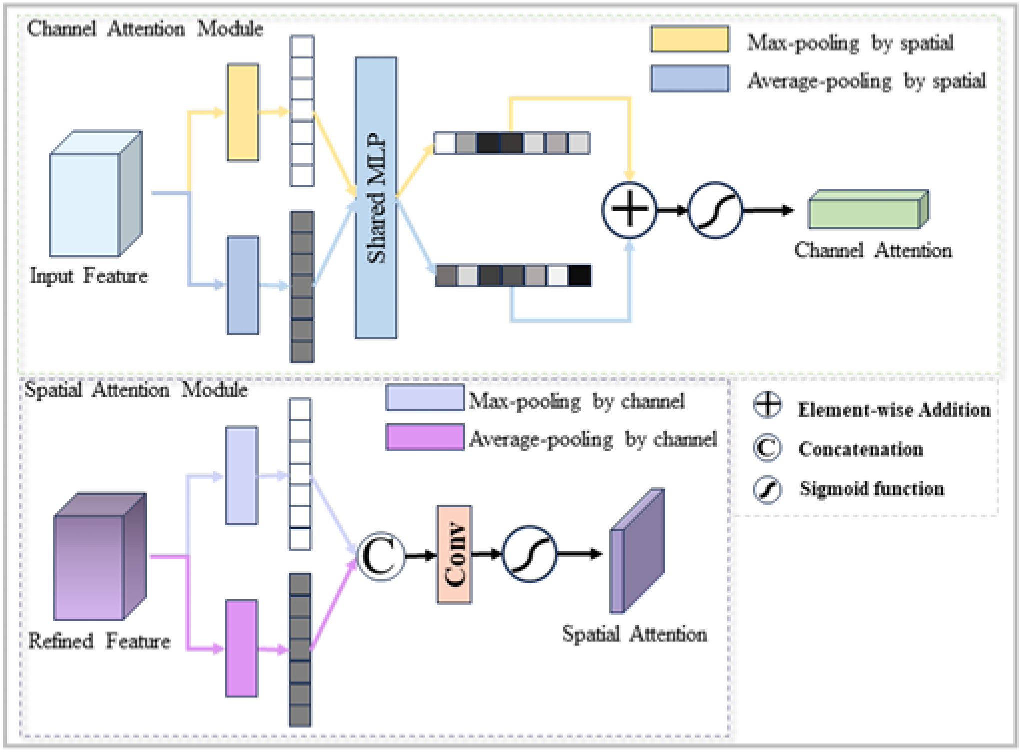

Fig. 2 Schematic diagram of module generation

2.3.2 Loss function design

In order to effectively train a high dynamic range image denoising model based on generative adversarial network, a multi-loss function that integrates the consideration of adversarial loss, content loss and structural loss is designed to comprehensively constrain the generator's generation process and improve the quality of denoised images. The adversarial loss is the core loss of the generative adversarial network, which makes the denoised image generated by the generator visually similar to the real noiseless image and able to fool the discriminator through the adversarial game between the generator and the discriminator. The relativistic loss treats the difference between the real image and the generated image as a relative disparity and more accurately measures the realism of the generated image. This approach enables the discriminator to better understand the realism of the generated image, improving training stability and the quality of the generated image. The loss function is expressed as follows:

$$L_G = -E_{x_r \sim p_{\text{data}}} \left[\log\left(D\left(x_r - E_{x_g \sim p_g}[D(x_g)]\right)\right)\right] - E_{x_g \sim p_g} \left[\log\left(1 - D(x_g - E_{x_r \sim p_{\text{data}}}[D(x_r)]\right)\right) \quad 2\text{-}1$$

$$L_D = -E_{x_r \sim p_{\text{data}}} \left[\log\left(D\left(x_r - E_{x_g \sim p_g}[D(x_g)]\right)\right)\right] - E_{x_g \sim p_g} \left[\log\left(1 - D(x_g - E_{x_r \sim p_{\text{data}}}[D(x_r)]\right)\right) \quad 2\text{-}2$$

Where x_r is the sample from the real data distribution$pdata$,x_g is the generated sample from the generator,p_g is the output distribution of the generator, and $(D\cdot)$ is the discriminator function indicating the authenticity of the input image.

The Charbonnier loss function introduces a square root into the error calculation, which makes the effect of large errors relatively small and therefore more robust to images containing noise or outliers. The mathematical form is as follows:

$$L_{\text{char}} = \sqrt{\|X_s - Y\|^2 + \epsilon^2} \quad 2\text{-}3$$

In addition, Ledge is the edge loss, defined as follows:

$$L_{\text{edge}} = \sqrt{\|\Delta(X_s) - \Delta(Y)\|^2 + \epsilon^2} \quad 2\text{-}4$$

where Δ denotes the Laplace operator.

Contrast learning is utilized to make the de-blurred output image close to its clear version and away from the input blurred image. The blurred input X, the deblurred result R and the clear version S are considered as negative, anchor and positive samples respectively. The loss formula is expressed as follows:

$$L_{\text{contr}} = \frac{L_1(\varphi(S) - \varphi(R))}{L_1(\varphi(X) - \varphi(R))} \quad 2\text{-}5$$

whereφ denotes the hidden feature extraction operation from the pretrained conv3-2 layer and$L$ 1 denotes the$L$ 1 paradigm. In the feature space, the contrast loss is minimized to keep the deblurring result R close to its clear version S (numerator) and keep R away from its blurred input X (denominator). The total loss function is expressed as follows:

$$L_{\text{total}} = \lambda_{GAN} L_{GAN} + \lambda_{\text{char}} L_{\text{char}} + \lambda_{\text{edge}} L_{\text{edge}} + \lambda_{\text{contr}} L_{\text{contr}} \quad 2\text{-}6$$

whereλGAN ,$\lambda c\ har$,$\lambda edge$,$\lambda contr$ denote the adversarial loss weights, Charbonnier loss weights, edge weights, and contrast loss weights, respectively. They are initialized to 0.001, 1, 0.05, 0.0005 respectively in the experiment.

2.4. Experimental data set

The high dynamic range image datasets used in this experiment are mainly derived from several public datasets and self-collected images. The public datasets include HDR+ Dataset, EPFL HDR Dataset, etc. These datasets cover a rich variety of scenes, such as natural scenery, urban street scene, indoor environment, etc., which provide a wide range of image samples for model training. Meanwhile, in order to further increase the diversity of the datasets, we have also collected a large number of high dynamic range images by ourselves using professional HDR cameras under different lighting conditions and shooting angles.

3 Results and analysis

3.1 Presentation of experimental results

In this experiment, peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) are used as objective evaluation metrics to quantitatively assess the denoising effect of the proposed Generative Adversarial Network-based image denoising algorithm for high-dynamic range images under different noise levels. Meanwhile, the proposed algorithm is compared with mean filter, median filter, Gaussian filter and denoising algorithm based on convolutional neural network (CNN) to verify the superiority of the proposed algorithm. The experimental results are shown in Table 1:

Table 1. Quantitative evaluation of denoising effect at different noise levels

noise level	Evaluation indicators	mean value filter	median filter
Low Noise(standard deviation ＝10)	PSNR (dB)	25.36	26.12
Low Noise(standard deviation ＝10)	SSIM	0.75	0.78
Medium noise(standard deviation ＝20)	PSNR (dB)	22.15	23.08
Medium noise(standard deviation ＝20)	SSIM	0.62	0.65
High Noise(standard deviation ＝30)	PSNR (dB)	19.87	20.56
High Noise(standard deviation ＝30)	SSIM	0.50	0.53

As can be seen from Table 1, the PSNR and SSIM metrics of this algorithm are better than mean filter, median filter and Gaussian filter under different noise levels. As traditional image denoising algorithms, mean filter, median filter and Gaussian filter are simple to compute, but it is easy to lose the detail information of the image during the denoising process, which leads to the blurring of the denoised image, and the PSNR and SSIM indicators are lower. Compared with the CNN-based denoising algorithm, this algorithm improves the PSNR by 1.76dB, 2.22dB and 2.31dB, and the SSIM by 0.03, 0.06 and 0.07 at low, medium and high noise levels, respectively, which indicates that this algorithm can remove the noise from the high-dynamic-range image more efficiently, and at the same time better preserves the image details and structural information, improving the quality of the denoised image. which improves the quality of the denoised image.

3.2 Comparative analysis of results

The denoising algorithm based on generative adversarial network proposed in this paper is compared with traditional denoising algorithms such as mean filter and median filter under the same experimental conditions. As shown in Fig. 3 and Fig. 4, from the objective evaluation indexes of PSNR and SSIM, under low noise level, the PSNR of mean filter is 25.36dB and SSIM is 0.75; the PSNR of median filter is 26.12dB and SSIM is 0.78; the PSNR of this paper's algorithm reaches 30.21dB, and the SSIM is 0.88. Under medium noise level, the PSNR of mean filter decreases to 22.15dB, and the PSNR of median filter decreases to 22.15dB, and the PSNR of median filter decreases to 22.15dB. Under the medium noise level, the PSNR of mean filter is 22.15dB and SSIM is 0.62; the PSNR of median filter is 23.08dB and SSIM is 0.65; and the PSNR of this paper's algorithm is 27.89dB and

SSIM is 0.82. Under the high noise level, the performances of mean and median filters are further degraded, and the PSNRs of mean filter and median filter are 19.87dB and 20.56dB, and the SSNR of this paper's algorithm is 20.56dB. 20.56dB and 0.50 and 0.53 respectively; the algorithm in this paper still maintains a good performance with PSNR of 25.43dB and SSIM of 0.75.

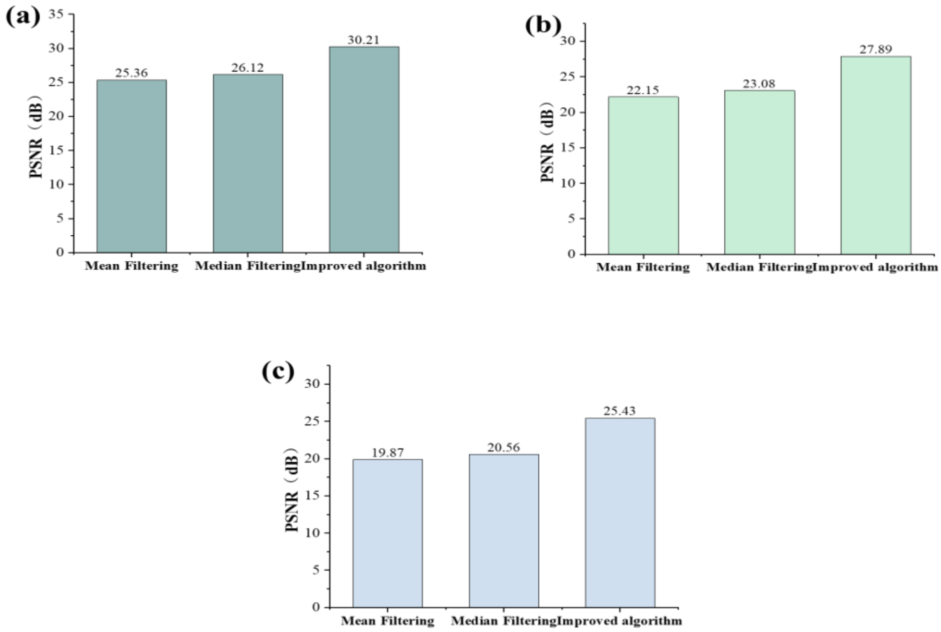

Fig. 3 Comparison of PSNR under three algorithms (a) low noise level (b) medium noise level (c) high noise level

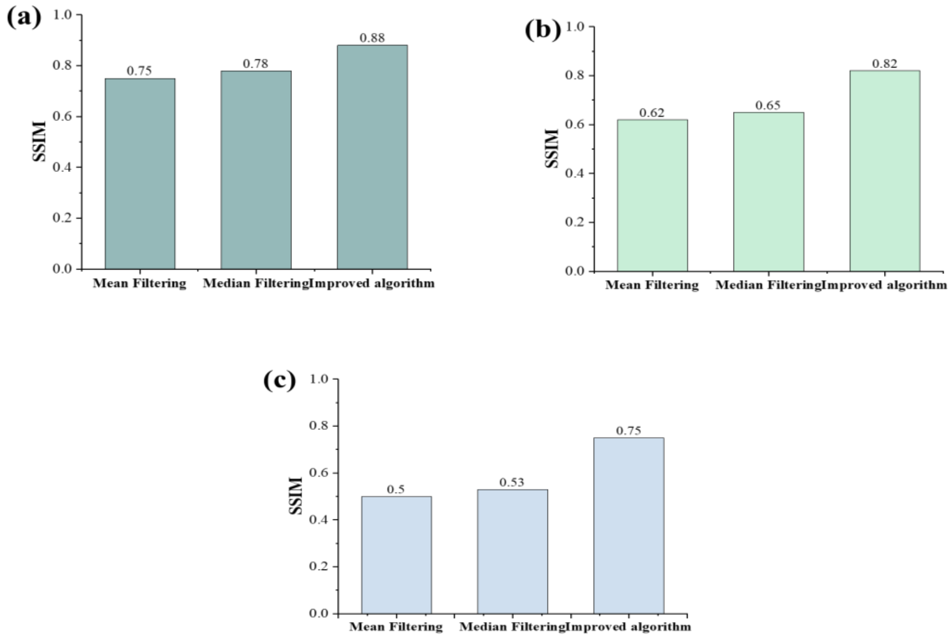

Fig. 4 Comparison of SSIM with three algorithms (a) low noise level (b) medium noise level (c) high noise level

From the visual effect, as shown in Fig. 5, although the noise is reduced in the image after mean filtering, the image becomes blurred and many detailed information is lost, such as in a high dynamic range image containing architectural details, the edges of the building become blurred after mean filtering, and the outlines of the windows are not clear. Median filtering is effective in removing impulse noise such as pretzel noise, but it is not effective in removing other types of noise such as Gaussian noise, and it is easy to cause loss of details and block effect when dealing with images rich in texture details, as in a natural landscape image with complex texture, the texture of the image after median filtering becomes unnatural, and there is a clear blocky area [10]. While the image processed by the algorithm in this paper, not only the noise is effectively removed, the details and structural information of the image are also well preserved, and the details of the image such as edges and textures are clearly visible under various noise levels, and the visual effect is significantly better than the traditional denoising algorithm.

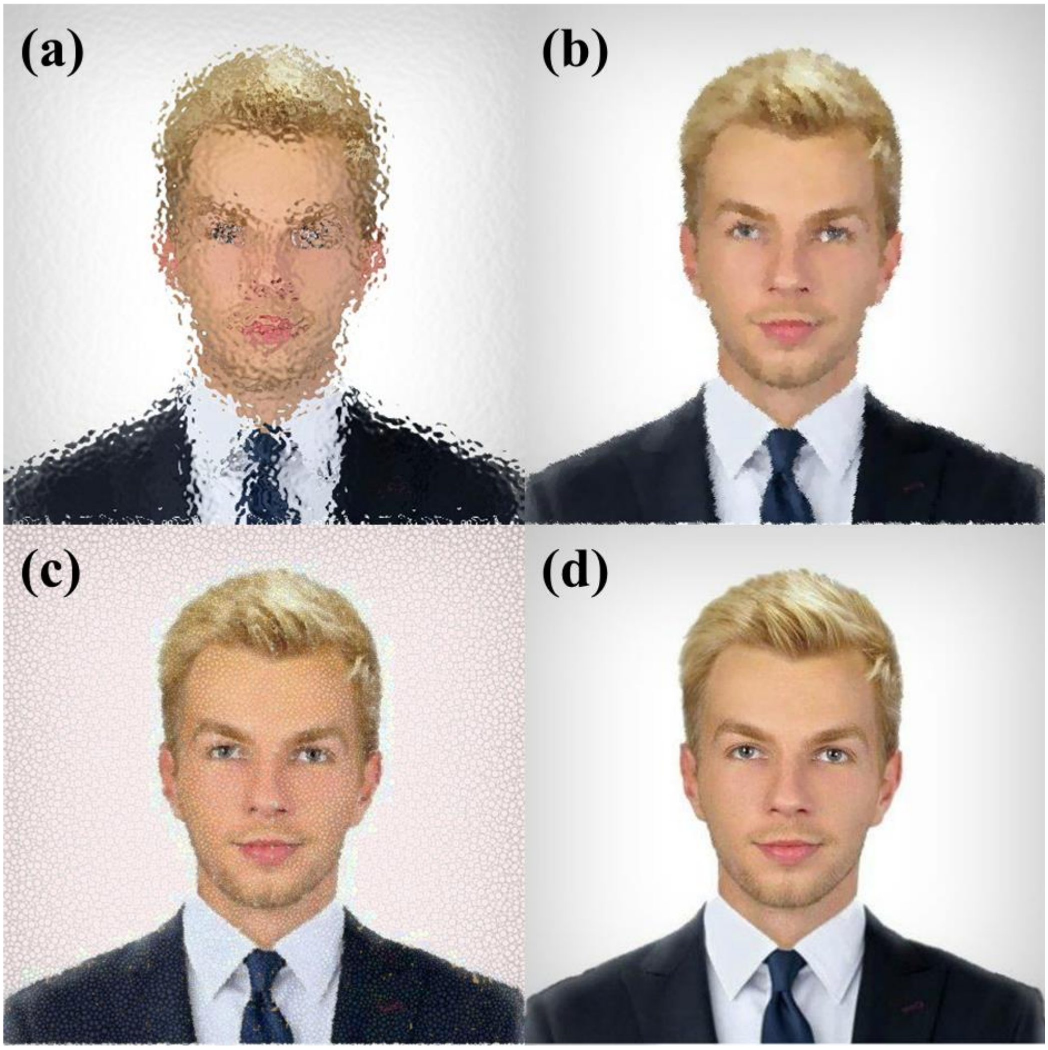

Fig. 5 Comparison of images under three algorithms (a) Experimental graph (b) Mean filtering (c) Median filtering (d) Improved algorithm

In summary, both from the objective evaluation index and the visual effect, the denoising algorithm based on generative adversarial network proposed in this paper is significantly better than the traditional denoising algorithms such as mean filtering and median filtering in terms of performance, and it can more effectively remove the noise in the high-dynamic-range image, while maintaining the details and structural information of the image.

3.3 Algorithm Performance Analysis

3.3.1 Algorithm validity

From the experimental results, the high dynamic range image denoising algorithm based on generative adversarial network proposed in this paper shows remarkable effectiveness in removing noise and preserving image details and structure. As shown in Fig. 6, the PSNR and SSIM values of this algorithm perform well at different noise levels on the objective evaluation metrics. At low noise level (standard deviation = 10), PSNR reaches 30.21dB and SSIM is 0.88; at medium noise level (standard deviation = 20), PSNR reaches 27.89dB and SSIM is 0.82; at high noise level (standard deviation = 30), PSNR reaches 25.43dB and SSIM is 0.75. The higher PSNR values indicate that the denoised image is better than the real noise-free image. Higher PSNR value indicates that the error between the denoised image and the real noise-free image is smaller, and the image quality is higher; while the SSIM value close to 1 indicates that the denoised image has a high similarity with the real noise-free image in terms of brightness, contrast and structure, and the structural information of the image has been retained effectively.

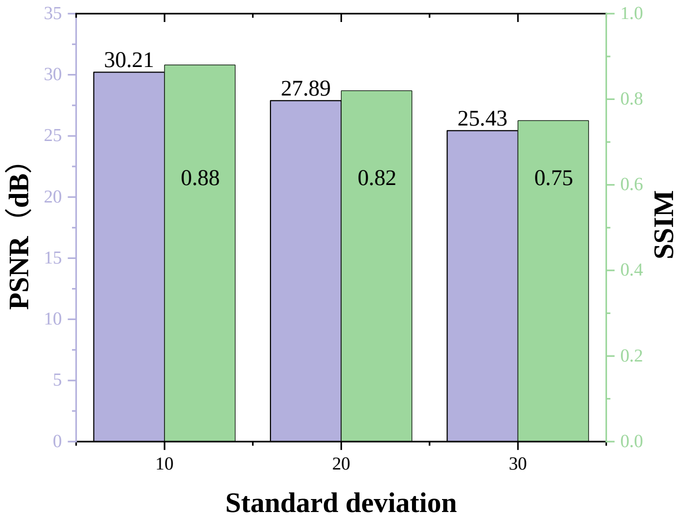

Fig. 6 Validity test of the algorithm

In terms of the actual image denoising effect, for high dynamic range images containing complex textures, such as the texture of ancient buildings, the veins of leaves, etc., the algorithm is able to remove the noise while clearly retaining the details of these textures, so that the denoised image texture is clear and natural, without blurring or loss of details. For images with obvious edge features, such as the outline of buildings, the edges of objects, etc., the algorithm can also accurately retain the edge information, so that the edges are clear and sharp, and the edges are not deformed or blurred due to denoising. This is due to the structural design of the generator in the algorithm, through the introduction of the attention mechanism, the generator can pay more attention to the key regions in the image, such as edges and texture regions, so as to better retain these important information in the denoising process; at the same time, the application of multi-scale feature fusion technology makes the generator able to make full use of the image features at different scales, and better adaptability to the complex noise and image structure. further improving the denoising effect and the ability to retain image details.

3.3.2 Algorithm Robustness

In order to evaluate the robustness of the new algorithm, experiments were conducted under different noise types and noise intensities. The experimental results show that the present algorithm has strong adaptability to different noise situations. In the face of Gaussian noise, the algorithm can effectively remove the noise and maintain the clarity and details of the image regardless of the change of noise intensity. Under low noise intensity, the algorithm is able to remove the noise almost completely, so that the image is restored to a state close to the real noise-free state; under high noise intensity, although the interference of the noise is large, the algorithm is still able to significantly reduce the impact of the noise, so that the quality of the image has been significantly improved, and the details and structure of the image are not seriously damaged. For pretzel noise, the algorithm also shows good robustness. It is able to accurately identify and remove pretzel noise points without negatively affecting the rest of the image. Even in the case of high density of pretzel noise, the algorithm can effectively restore the original appearance of the image, preserving the details and structural information of the image. This is because the algorithm learns from a large amount of image data with different noise types and intensities during the training process, which enables the network to fully understand the characteristics and distribution laws of various noises, so that when faced with different noises, it can automatically adjust the denoising strategy to target the removal of the noise without overly damaging the original information of the image. In addition, this algorithm can also achieve better results when dealing with mixed noise (i.e., containing multiple noise types at the same time) in high dynamic range images. It is able to consider the characteristics of different noises comprehensively, remove multiple noises simultaneously, and restore clarity to the image, demonstrating strong robustness and adaptability.

4 Conclusion

In this study, a new algorithm for high dynamic range image denoising based on generative adversarial network has been successfully designed and implemented, and a series of innovative and practical research results have been achieved in the field of image denoising. In terms of algorithm design, the structure of the generative adversarial network is innovatively optimized. Enhanced ability to retain image details. The authenticity of the generated image is judged more effectively, and the antagonistic effect of the generative adversarial network is improved. In terms of loss function design, a multi-loss function optimization strategy that comprehensively considers the adversarial loss, content loss and structure loss is proposed. The adversarial loss makes the generated denoised image visually similar to the real noiseless image through the adversarial game between the generator and the discriminator. By reasonably adjusting the weight of each loss term, effective constraints on the generator are realized, and the quality of the denoised image is improved. Compared with the traditional denoising algorithms such as mean filter, median filter and Gaussian filter, this algorithm has significant advantages in objective evaluation indexes such as PSNR and SSIM, and it can remove the noise more effectively, while retaining the details and structural information of the image better, and the visual effect of denoised image is obviously improved. The denoising time of a single image in the testing stage is short, and the memory consumption is within the acceptable range, which can meet the requirements of practical applications.

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There are no relevant economic interests and no other potential conflicts of interest.

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