Effect Analysis of Fourier Transform and Neural Network on Image Noise Reduction

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Abstract. During the acquisition, transmission, and processing of digital images, noise often appears in the pictures, seriously affecting the quality of the images and the accuracy of subsequent analysis. To solve this problem, many scholars have conducted in-depth research on image denoising, aiming to find denoising methods suitable for different scenarios. This study aims to compare the effects of Fourier transform and neural network methods in eliminating stripes in pictures. The discrete Fourier transform denoising method performs best in sharpness and has a fast processing time, but its image restoration is poor. Although the artificial neural network method has a long processing time and depends on the training set, it has good noise reduction effect. The Photoshop (beta) method is relatively simple and easy to use, with good overall effect. It is hoped that through further research, a better understanding of the role of Fourier transform and neural network methods in image noise elimination can be achieved, providing more references for the development of image processing technology. This article introduces in detail the Fourier transform method and neural network method, analyzes their advantages and disadvantages and scope of application. These results shed light on guiding further exploration of noise reduction.

Keywords: Noise Reduction; CNN; Fourier transform.

1. Introduction

When an image is generated, a certain amount of noise is generated. It refers to undesirable random interference or distortion in an image, usually in the form of irregular brightness or color changes. Interference can significantly reduce the quality and visualization of an image, making it blurry, distorted, or illegible. There are many types of image noise, including color fine noise generated by the equipment production process or low-light environment, and fringe noise generated by specific environments such as electromagnetic environments. The cause of image noise involves many factors, which can occur at various stages, such as image generation, transmission, and processing. Image noise not only has a significant impact in photography, videography, medical imaging, etc., but also interferes with applications such as image analysis, computer vision, and pattern recognition. In the field of digital image processing, there are methods and devices that can be used to denoise and reduce the complexity of images while maintaining the noise reduction effect [1].

Image noise reduction is an important research direction in the field of digital image processing, aiming to reduce noise in images to improve the visual effect of images. Its research history dates back to the 1970s. In the early stages, the linear filters techniques were mainly used to blur the image and thus reduce the effect of noise. However, these methods tend to cause blurring of image details. With the development of computers, in the 1990s, more complex nonlinear filtering techniques were invented. Subsequently, wavelet transforms have also been introduced into the field of image noise reduction, which can decompose the image into components of different frequencies, so that noise and signal can be better separated. However, the above two methods still have limitations, mainly the selection of filter parameters and the problem of wavelet artifacts. The filtering method requires the selection of appropriate parameters, such as filter size, weight, etc. Under different image and noise conditions, parameter selection can become complex and difficult to generalize. In wavelet transforms, low-frequency components are generally well preserved, but high-frequency components (detail) can show artifacts and noise reduction is less than ideal. In recent years, with the development of artificial intelligence, more complex technologies such as neural networks and Fourier transforms have also been applied to the field of noise reduction. The difficulty in this area is that noise is a combination of factors, and its production stage is not fixed, which add the challenge of mitigating the effects of image noise. At present, various algorithms and technologies for image denoising have been developed, including deep learning methods, Fourier transforms, artificial intelligence models and sparse regularization denoising algorithms, which can eliminate image noise to different degrees based on different principles, while retaining the structure and detail information in the image [2-4].

Both the Fourier transform, and neural networks can denoise the image. At present, there are many derivative algorithms for Fourier transform noise reduction. As early as 2013, scholars have proposed a method to reduce image noise using Fourier wavelet transform and context-based models [2]. Then Hogasten Nicholas created a method that involves performing first and second spectral transformations on subsets of row values in an image frame to determine spectral coefficients, the second spectral coefficient is selectively adjusted to reduce the noisy information in the image [3]. It has also been proposed that a new method of enhancing terahertz image quality using the correlation function (convolution function) between the Fourier transform of an image and the Fourier transform of a standard image that may be complex enough can be used to remove noise and improve image quality [4]. Some scholars have proposed a more complex method, that is, first use the image deblurring method based on Fourier transform, use the K-SVD algorithm for pre-denoise, and then perform internal and external iterations to obtain the final denoising image. It uses Fourier transform to obtain good noise reduction results, which also obtains better optimization results [5].

Deep convolutional neural networks (CNNs) can also be used for image noise reduction. This method is usually trained on a preset test set with a large amount of data, and then applied, or use GainTunning to adaptively adjust a pre-trained model of a single test image. Well-trained deep neural network achieves excellent performance, but it is difficult for them to generalize to data that deviates from the training distribution. Recent studies have shown that denoisers can be trained on a single noisy image, which allows the model to adapt to the features of the test image. These networks can effectively remove noise from specific types of patterns or textures. In addition, a graph neural network architecture has been introduced to denoise signals defined on irregular domains such as graphs. A self-supervised deep learning method for image denoising is also proposed, which does not require a high dose of reference images for training. These methods can effectively remove noise and improve image quality [6-10].

Noise in pictures often occurs during digital image acquisition, transmission and processing, which seriously affects image quality and accuracy of subsequent analysis. Many scholars have studied image noise reduction in depth, aiming to find noise reduction methods suitable for different scenes. These methods include traditional methods based on signal processing techniques, as well as new methods based on neural networks. These methods have achieved some results to varying degrees, but there are also some limitations and challenges, some methods achieve good noise reduction in certain situations, they may not perform well in others. The noise reduction methods based on deep learning and neural networks, which train neural networks with a large amount of data, can better capture features and patterns in images, resulting in more accurate noise reduction. This paper aims to compare the effects of Fourier transform method and neural network method in image stripe removal and study the application of these two methods in different scenarios, and further explore their performance differences and possible influencing factors. This research provides a comprehensive understanding of Fourier transform and neural network in image noise reduction and provides reference for the development of image processing technique.

In the following chapters, Fourier transform methods and neural network methods will be introduced in detail, and their advantages and disadvantages and their scope of application will be analyzed. In the Data and Methods section, this study will describe in detail the source of image data, as well as noise reduction methods based on Fourier transform and machine learning. Next, this paper will present and discuss the experimental results, including noise reduction effects based on Fourier transform and machine learning. In the discussion section, this research will compare the results of different methods and explore the practical application implications of these results and possible directions for improvement. In the Limitations and Future Outlook section, this study will point out the limitations of the current approach and look ahead to possible future directions in this area. Finally, this study will summarize the findings, limitations, and implications.

2. Data and Method

2.1. Method Based on FFT Processing

The noise reduction method based on Fourier transform is a traditional and effective image processing technique, which reduces noise and interference in the images through frequency domain analysis. The core idea of this method is to convert the image into the frequency domain, use the frequency domain information to eliminate or suppress noise, and then convert the image back to the time domain. Among them, the Fourier transform is the basic tool, which can convert the image signal in the time domain into spectral information in the frequency domain [11]. The mathematical expression of the Fourier transform is as follows:

$$F(u,v) = \iint_{-\infty}^{\infty} f(x,y) e^{-i2\pi(uv+vy)} dxdy \tag{1}$$

Where F is the complex number of spectra in the frequency domain, f is an image in the time domain, (u, v) is the frequency coordinates. By performing a Fourier transform on the image, one can obtain information about the image at different frequencies.

In noise reduction methods based on Fourier transform, a common strategy is to utilize filtering operations in the frequency domain, using a high-pass filter to reduce low-frequency noise, or a low-pass filter to remove high-frequency noise. In practical applications, noise suppression can be achieved by designing different types of filters. One of the most common Fourier domain filters is the ideal filter, whose frequency response is defined as:

$$H(u,v) = \begin{cases} 1, D(u,v) \le D_0 \\ 0, D(u,v) > D_0 \end{cases} \tag{2}$$

Where H is the frequency response of the filter, D is the distance from (u, v) to the origin, D_0 is the cut-off frequency, which controls the passband range of the filter.

2.2. Method Based on Machine Learning

The noise reduction method based on neural network is a method that has achieved remarkable results in the field of image processing in recent years. Through deep learning techniques, neural networks can automatically learn features and patterns in images to achieve more accurate noise reduction. Among them, Convolutional Neural Network (CNN) is the most widely used type of neural network, which performs well in image processing tasks [12, 13]. The core idea of neural network is to learn and extract image features at various scales through a series of convolutional, pooling and fully connected layers, so as to achieve image noise reduction. In noise reduction methods based-on neural network, an autoencoder structure is usually used, in which the encoder maps the input image to a low-dimensional feature space, and the decoder reconstructs these features into an output image. Through training, the network learns how to remove noise and retain useful information about the image. The mathematical expression of the autoencoder is as follows:

$$h = f(Wx + b) \tag{3}$$

$$\hat{x} = g(W'h + b') \tag{4}$$

Here, x is the input image, h is the output of the encoder, $\hat{x}$ is reconstruction output of the decoder, W and W' is the weight matrix, b and b' is the bias vector, f, g are the activation functions such as ReLU or Sigmoid. In addition, in order to better deal with noise, the noise reduction problem can be transformed into a loss minimization problem, that is, the network is trained by minimizing the difference between the input image and the reconstructed image. Common loss functions include

Mean Squared Error (MSE) and Structural Similarity Index (SSIM). Neural network-based noise reduction methods have certain advantages, especially when dealing with complex noise and image structures.

3. Results and Discussion

An image with high noise is taken as the object to process the noise reduction. The image was taken by the Nikon D850, in order to compare the noise reduction effect, and noise was added through Photoshop in the later stage, obtain the original image (seen from Fig. 1). Then, Fourier noise reduction and artificial neural network noise reduction are carried out on Fig. 1 respectively, and the built-in noise reduction function of Photoshop is also used to reduce the noise of Fig. 1, and the restoration degree of image details under the same amount of noise are compared.

Fig. 1 Raw image with added noise

3.1. Method Based on FFT Processing

Using Fourier transform to denoise color images, choose Python to write programs. First, the image is decomposed into three color channels, and then the discrete Fourier transform is performed on each color channel. A low-pass filter is then designed and applied to the frequency domain of each color channel. In the frequency domain, the different frequency components of the signal can be clearly distinguished, and the noise components in the signal can be removed by designing suitable filters. Finally, the processed frequency domain signal is converted back to the time domain, and the processed color channels are merged into a color image. In this program, a low-pass filter is used to remove the high-frequency noise components in the image, so as to achieve the purpose of noise reduction. The parameters selected for this filter are the same for the three colors R, G and B, and the results under the condition that the filter parameters are 30 and 120 respectively are shown in Fig. 2.

Fig. 2 Comparison of images before and after denoising with Fourier transform

As can be seen from Fig. 2, when the filter parameter is 30, the noise reduction result is not ideal, and the color of the image after noise reduction is seriously deviated from the original image, and the details are also seriously missing. After changing the size of the filter to 120, the obtained noise reduction image has obvious retention in detail, but the color is still quite different from the original image. Some highlight areas of the original image are shown as shadow areas in the image after noise reduction. The color of the original image is mainly yellow, and the image after noise reduction is mainly blue. It is believed that this is caused by the color reverse problem, so a new color reverse correlation code is added to the program and tested again. The results are shown in Fig. 3. It can be seen that its exposure has serious deviation.

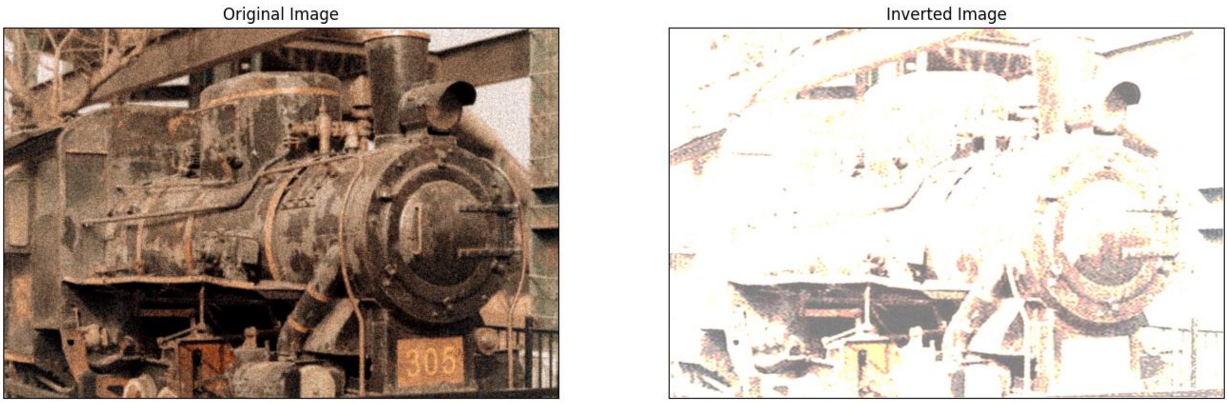

Fig. 3 Comparison of images before and after color reverse denoising with 120 size filter

Considering that the color of the original image is mainly yellow, and the three colors R, G, and B in the above algorithm use the same filter, the filter may over-intercept the red and green high frequency parts but has a better filtering effect on the blue high frequency parts. Therefore, filters of different sizes were set for the three-color components, the program was modified again, and histogram optimization was carried out after noise reduction. The results obtained during operation were illustrated in Fig. 4. As can be seen from Fig. 4, the exposure color of the image is still quite different from the original image. The adjustment of the filter is also more complicated, and the result is not ideal, possibly because the filter size of the selected R, G, and B is different from the optimal size. The images used in this experiment are mainly yellow colors, so it may be better to filter images with more balanced colors by using discrete Fourier transform.

Fig. 4 Comparison of images before and after three color denoising respectively and the histogram optimization.

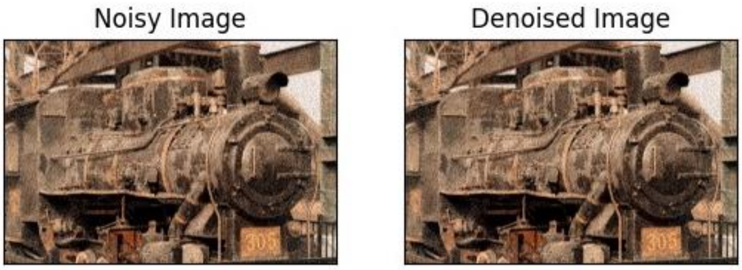

Fig. 5 Comparison of images before and after convolutional neural network denoising.

3.2. Method Based on Convolutional Neural Network

Convolutional neural network (CNN) was used for image denoising, and Python was used for programming. The Keras is used in the program to build and train a neural network model for de-noising input images. First, a convolutional neural network model is defined, which includes input layer, convolutional layer and output layer. The input layer receives the noisy image as input, the convolutional layer processes the image to remove the noise, and outputs the denoised image through the output layer. The model is trained with loaded training data (noisy images and clean images), learning how to remove noise from the input images by constantly adjusting the parameters to minimize the loss function during training. Finally, the program loads the image with noise (Fig. 1) and uses the trained model for noise reduction. The results are presented in Fig. 5. As can be seen from Fig. 5, after neural network noise reduction, the picture detail retention degree is better, and the color restoration degree is higher. However, running this algorithm requires a large amount of computing power. Although it gets a good result, it has a high time complexity.

3.3. Noise Reduction using Photoshop

Photoshop (beta) was used for noise reduction. The image can be reduced through its CameraRaw filter. Appropriate parameters were selected, and the results were presented in Fig. 6. It is found that the degree of detail retention is slightly worse than that of the artificial neural network method. But the algorithm is extremely fast and produces very accurate color reproduction.

Fig. 6 Image after denoising with Photoshop (beta)

3.4. Comparison and Implication

The denoising effects of discrete Fourier transform, convolutional neural network (CNN) and Photoshop(beta) are compared in Table 1. Discrete Fourier transform can better preserve the lines and boundaries in the image through the selection of filter parameters, and the clarity of the lines affects the sharpness of the image. The convolutional neural network algorithm has high time complexity, high detail retention, and the comprehensive noise reduction effect is close to that of Photoshop(beta). Photoshop(beta) has the best overall noise reduction effect, but it still has the problem of low detail retention. If the discrete Fourier transform denoising can be combined with the other two algorithms to enhance the artificial neural network or Photoshop(beta) denoising results with the image boundaries and lines obtained by the discrete Fourier transform, it is expected to have better results.

Table 1. Comparison of denoising effects of discrete Fourier transform, convolutional neural network (CNN) and Photoshop(beta)

Denoising method	details	Comprehensive denoising effect	Operation speed	Complexity of operation
Discrete Fourier transform	low	bad	medium	medium
Convolutional neural network	high	good	low	complex
Photoshop(beta)	medium	good	fast	easy

4. Limitations and Prospects

For images denoising, it is clear that the method of high-frequency filtering after discrete Fourier transformation is not very effective. The reason is most likely due to the inappropriate selection of filter parameters. Considering that many attempts have been made to adjust the filter size and various parameter during program writing, it can be concluded that this method has a good suppression effect on noise points while also retaining good image sharpness. However, its disadvantage is that too much high-frequency information is eliminated in the frequency region during denoising, which corresponds to the information of the dark and shadow parts in the time domain, making the picture obviously brighter than the original picture. At the same time, the overall color of the image also affects the noise reduction effect of the method.

The noise reduction method using CNN is not very friendly to individual users, because it requires a large number of pictures as a training set and requires equipment with high computing power to train CNN. At the same time, this method takes much longer than using discrete Fourier transformation for denoising. However, this method has good denoising results and has a low correlation with the color of the picture. It also has a low dependence on parameters. The noise reduction software that comes with Photoshop(beta) has a very high noise reduction speed and poor detail retention in high noise situations. Nevertheless, when the number and size of noise points are low, it has a good image restoration effect. In future research, more image noise reduction methods can be explored, and various methods can be combined to improve image quality. In addition, these methods can be applied to different types of image data to verify their universality and effectiveness.

5. Conclusion

To sum up, this paper investigates the effectiveness of Fourier Transform and Neural Network on image noise reduction. According to the analysis, discrete Fourier transform denoising method has the best performance in sharpness and faster processing time, but its image restoration is poor. Although the artificial neural network method has a long processing time and depends on the training set, it has a good denoising effect. The Photoshop(beta) method is relatively simple and easy to use, and the overall result is good.

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