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Research on image restoration algorithms based on BP neural network ☆

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ABSTRACT

With the development of information transmission technology and computer technology, information acquisition mode is mainly converted from character to image nowadays. However, in the process of acquiring and transmitting images, image damage and quality decrease due to various factors. Therefore, how to restore image has become a research hotspot in the field of image processing. This paper establishes an image restoration model based on BP neural network. The simulation results show that the proposed method has made a great improvement compared with the traditional image restoration method.

1. Introduction

In today's information society, information acquisition and utilization has become increasingly important, and image is the main source of human access to information. Research shows that more than 80% of human access to information from the outside world comes from visual-related information. With the rapid development of various imaging sensor technologies, people are often exposed to a variety of images in real life, such as natural scene images taken by ordinary cameras, sequence images recorded by video surveillance cameras, infrared images taken by infrared sensor cameras. And radar images obtained by various imaging radar systems. However, in the process of image formation, transmission and storage, image quality is degraded due to various factors affecting the imaging system. This phenomenon is called image degradation.

There are many factors causing image degradation, including random atmospheric turbulence, relative movement of camera and target, poor focus of camera, sensor noise, aberration of optical system, physical limitation of imaging equipment, spectrum aliasing and so on. The typical manifestations of image degradation are image blurring, noise, resolution degradation, geometric distortion, block effect and mosaic phenomenon, which bring great difficulties to subsequent higher-level image processing (such as image segmentation, image registration, etc.). How to reduce or even eliminate the influence of degradation factors on image quality and improve the resolution, clarity and signal-to-noise ratio of image has become an issue of great concern to scholars and engineers in the field of image processing. For this reason, a new research field, Image Restoration, has emerged.

Image restoration uses the prior information of image degradation to establish a mathematical model of image degradation, and then processes the degraded image along the inverse process of image degradation to restore and reconstruct the original ideal image. Image restoration is a basic task in the fields of image processing, pattern recognition and computer vision. In recent decades, this technology has been deeply applied to space exploration [1,2], astronomical observation [3,4], remote sensing image [5,6], material research [7,8], industrial detection [9,10], medical image [1,12], military target recognition [13,14], case detection [15,16] and other fields of science and technology have greatly promoted the development and progress of human science and technology.

Because there are many factors affecting image quality, the research on image restoration is also more extensive. Generally speaking, the typical problems of image restoration include image noise removal, image blurring removal, image super-resolution reconstruction, image mosaic removal and image compression sensing reconstruction. Traditional image denoising methods are mainly divided into two categories: one is spatial domain filtering denoising, the other is frequency domain filtering denoising. Mean filtering, Gauss filtering and Wiener filtering are representative methods of spatial denoising. The basic idea is the correlation of adjacent pixels: based on spatial filtering, the gray level of a pixel

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in an image is determined by all the pixels in a certain range of neighborhoods. These methods are effective in dealing with simple noises, but they have serious shortcomings: due to the use of neighborhood mean, it is bound to smooth the edges, details and other important features of the image. In frequency domain, band-stop filters can effectively eliminate periodic noise; band-pass filters perform operations contrary to band-stop filters.

Although the traditional image restoration method is simple and effective, it is aimed at simple image denoising. Generally speaking, image degradation is a complex process, and the above restoration methods are seldom used in practice. From the Bayesian point of view, when the likelihood probability of the image is known, the prior probability of the image will play a vital role in the image restoration results. Many models have been built to acquire prior knowledge of images, including non-local self-similarity model, sparse model, gradient descent model and Markov random field model. Among them, the advantages are as follows: BM3D (Block_of_3-Dimension) algorithm, LSSC (Learned_Simultaneous_Sparse_Coding) algorithm, WNNM (Weighted Nuclear Norm Minimization) algorithm, etc. BM3D is a three-dimensional block matching cooperative filtering algorithm which combines local and non-local information correlation of images.

NCSR algorithm in sparse model utilizes image non-local self-similarity. Image denoising, image deblurring and image super-resolution reconstruction have good results. WNNM algorithm can deal with different noise levels even for specific image restoration directions, such as image denoising. In order to avoid the disadvantage of choosing the model parameters, the researchers put forward a method of de-noising based on discriminant learning. Schuler et al. proposed MLP_ (Multi-layer Perceptron) model [17], which combines image preprocessing with multi-layer perceptron neural network learning model. Firstly, the degraded image is deblurred in frequency domain. This process can largely achieve the purpose of image restoration. Then, MLP neural network is used to optimize the noise removal and the ringing effect in the process of deblurring. Schmidt et al. proposed the CSF_model [18]. They combined the splitting algorithm with the random field model and integrated it into a single learning framework. Chen et al. [19,20] proposed the Trainable Nonlinear Reaction Diffusion model, which expanded sparse coding and iteration methods into forward feedback networks, and achieved good image restoration results. In real image denoising, there are also deep learning algorithms. Nam et al. use MLP [21] to train the noise distribution in real noise image, and then use Bayesian non-local mean filter algorithm to denoise. (Bayesian_Nonlocal_Means_Filter).

For image deblurring, it is usually modeled mathematically as the convolution of the blur kernel (also known as point spread function) and the original image, and noise is usually added. Point spread function is not necessarily known in advance, so the degree of understanding of point spread function determines the difficulty of image deblurring to a certain extent, so there are two types of image deblurring: one is that the point spread function is known beforehand, which is called non-blind image deblurring; The other is blind image deblurring with unknown PSF in advance. The latest regularization technology is used to solve the problem of image denoising, but Rudin et al. extended it to the problem of non-blind image restoration. Following the successful application of the total variational model to the problem of non-blind image restoration, the blind restoration model based on the total variational norm is further proposed. Fergus and others have also done pioneering work by fitting the "peak and heavy tail" characteristics as a priori knowledge of images.

In the late 1960s, Bryson et al. put forward the idea of error back propagation. With the deepening of the research on neural networks, more and more scholars have carried out further research on the basis of the idea of error back propagation. In the mid-1980s, people began to attach importance to the algorithm of error back propagation based on the research results of Rumelhart and others, and gradually applied to military, market analysis, graphics and image processing and other fields. In 1986, as a classical artificial intelligence algorithm, BP neural network algorithm was first mentioned in Parallel Distributed Processing published in 1986. The heat generated by the error reverse propagation algorithm mentioned in PDP has lasted up to now. Artificial Neural Network (ANN) algorithm has undergone a tortuous process from boom to trough and then to the second boom. In 1988, Zhou summarized J.J. Hopfield's Hopfield model of interconnected nonlinear dynamics and thought that it could be constructed by discrete Hopfield neural network in image restoration. Since then, this kind of neural network algorithm called feedback has been applied in digital image restoration [22–26].

BP neural network has the advantages of simple network structure, strong operability, arbitrary non-linear fitting for input and output, which makes it possible to use in image recognition, information prediction and pattern recognition [32–36]. In recent years, BP neural network has been widely used in image processing research. This paper studies how to improve the effect of image restoration by establishing an image restoration model based on BP neural network. The simulation results of Lena image and real environment image show that the proposed method can effectively improve the similarity of image restoration.

2. Methods

2.1. Image degradation

Image restoration is to recover a solution as close as possible to the original image from the blurred noise image [27–31]. Image restoration is an ill-posed problem. A small change in data may lead to a large error. How to transform the image restoration problem into an appropriate problem and give a fast and stable numerical solution is the main research objective of this paper. Due to environmental factors and limitations of physical imaging equipment, image degradation is inevitable in the acquisition process [37–39]. The image can be expressed as a two-dimensional brightness function. This paper marks the two-dimensional brightness function as $f(x,y)$, the process of image degradation can be described as the degraded image generated by the action of fuzzy operator H and noise $n(x,y)$ on the original image $u(x,y)$. If the fuzzy operator is linear and space invariant, the image degradation process can be expressed as:

$$f(x,y) = H(x,y) * u(x,y) + n(x,y) \tag{1}$$

where * denotes convolution.

Fuzzy kernels are also called point spread functions. Different image blurring problems correspond to different point spread functions. In practical applications, the point spread function is unknown, which needs to be estimated first when restoring the image. Therefore, the accuracy of the estimated point spread function determines the quality of the restored image. Fortunately, the point spread function in daily life is very limited, which greatly reduces the difficulty of estimating the point spread function. The Gauss Fuzzy Point Diffusion Function selected in this paper can be expressed as follows:

$$H(x,y) = \frac{1}{\sqrt{2\pi}\sigma}\exp(-\frac{x^2+y^2}{2\sigma^2}) \tag{2}$$

Among them σ is the Gauss fuzzy variance.

2.2. Image denoising

In digital imaging, the main source of noise is the electronic imaging system itself. According to the central limit theorem, most of these noises approximate the normal distribution, that is, the Gauss distribution. Therefore, Gauss noise has attracted wide attention. Its probability density function is expressed as follows:

$$p(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{(x-\mu)^2}{2\sigma^2}} \tag{3}$$

where x denotes the brightness value of noise n, μ is the average or expectation denoted, and σ is the standard deviation denoted. Gauss white noise is a special case of Gauss noise. Its probability density function obeys the standard normal distribution, namely $\mu = 0$.

2.3. BP neural network

Back Propagation Neural Networks (BP Neural Networks) is a multi-layer feedforward artificial neural network, which is trained by error back propagation algorithm proposed by Rumelhart and McCelland in 1986. At present, the subject of BP artificial neural network is more and more extensive, such as the physiological and psychological aspects of medicine, and the establishment of theoretical models and network models and algorithms. BP neural network can learn and store a large number of functional relationships before and after data input, without the function relations determined in advance, only through data training. BP neural network revises the weights and thresholds of the network by back propagation to reduce the error between the output value and the expected value. The topology of BP neural network includes input layer, hidden layer and output layer.

BP neural network algorithm is a supervised learning algorithm, that is, the actual output value of the output layer does not match the expected output value, and the error back-propagation is carried out immediately. The algorithm is based on the least squares method, namely LMS algorithm, which uses the method of moving forward layer by layer, so that the square of error between the output value and the expected value is within the threshold value range.

(1) Structure Definition of BP Network

The number of neurons in the input layer is n, the number of neurons in the hidden layer is p, and the number of neurons in the output layer is q.

(2) Data Variable Definition of BP Network

Set N input layers and assume that the input vector is $x = (x_1, x_2, ..., x_n)$, the implicit layer data is assumed to be $h = (h_1, h_2, ..., h_p)$, the output data of the implicit layer is $ho = (ho_1, ho_2, ..., ho_p)$, the input data of the output layer is $y = (y_1, y_2, ..., y_n)$, and the output data of the output layer after simulation is $yo = (yo_1, yo_2, ..., yo_n)$, and the expected output data of the output layer corresponds to the input sample is $eo = (eo_1, eo_2, ..., eo_n)$.

(3) Calculating the partial derivative of the error function of the sample data to the neurons in the output layer;
(4) The partial derivatives of the error function to the hidden layer neurons are calculated by the calculation results of the above steps.
(5) The output value of the hidden layer is calculated by the partial derivative of the error function to the neurons in the output layer.
(6) Calculate the corrected connection weight. If the error function is e and the iteration partial derivative of each neuron is$\delta_o(k)$, marked as$w_m(k)$is the corrected weight, the formula for calculating the variable value$\Delta w(k)$ is as follows:

$$\Delta w(k) = -\mu \frac{\partial e}{\partial w} = -\mu \frac{\partial e}{\partial hi(k)} \frac{\partial hi(k)}{\partial w} = \delta(k)x(k) \tag{4}$$

(7) If the global error is defined as E, the calculation method of E is as follows:

$$E = \frac{1}{2m} \sum_{k=1}^{m} \sum_{o=1}^{q} (d_o(k) - y_o(k))^2 \tag{6}$$

(8) The global error E is used to judge that four copies are up to expectation, and if they are up to expectation, they will end, or they will return to the input and output of calculating hidden layer neurons.

3. Experiment

In order to illustrate the superiority of the proposed algorithm, the experiment of non-local mean denoising for 256 * 256 Lena images is carried out. Motion blur and Gauss white noise are added to the image respectively. In order to make a fair comparison, the Gaussian weighting is replaced by the smoothing kernel, which is the standard Euclidean distance. The quality evaluation of denoised image is based on the measurement of SSIM by PSNR and structural similarity index. The formula for these two criteria is

$$PSNR(P, I) = 10\log(\frac{P_{\max}^2}{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(P_{i,j} - I_{i,j})^2} \tag{7}$$

$$ssim(P, I) = \frac{1}{mn} \frac{(2\mu_p\mu_i + C_1)(2\sigma_{pi} + C_2)}{(\mu_p^2 + \mu_1^2 + C_1)(\sigma_p^2 + \sigma_i^2 + C_2)} \tag{8}$$

Formula μ_p and μ_i is the mean of 8 * 8 blocks of restored image and original image, m and n denote the size of image, σ denotes the standard deviation of corresponding subscripts, and σ_{pi} denotes the covariance, C_1, C_2, C_3 is a constant.

Determination of the number of neurons:

This operation uses three-layer BP neural network. At present, there is no theoretical support for determining the number of neurons and network layers. Generally, the network is constructed first, and the number of different network neurons and network layers are set. Every time the number of neurons and network layers are set, experiments are carried out to compare the error accuracy of the experimental results. However, when the number of neurons and layers are selected in the experiment, a range should be set. Generally, within the acceptable error range, the number of neurons in the hidden layer should be minimized. For the selected experimental data, the number of neurons in the hidden layer of the neural network is increased in turn from small to large. First, a small number of neurons are set up to carry out experiments, and then gradually increase until the experimental error is within the allowable threshold. A BP neural network with three layers can approach any continuous function in any non-unbounded region if the number of neurons in the hidden layer is large enough. Therefore, the more neurons, the better the expected goal. However, the accompanying problem is that when the number of neurons is too large, the training time may increase, and the structure of the neural network is not easy to converge.

4. Results and discuss

One of the main technical problems in image restoration is image degradation. The main cause of image degradation is image blurring. The blurring caused by scene and sensor can be processed by low-pass filtering in spatial domain or frequency domain. For image blurring caused by uniform linear motion between sensor and scene in image acquisition process, this paper uses TPT function in MATLAB to process. In order to verify the feasibility of this method, this paper uses Lina head image as the material to process Gauss noise and motion blurring. The results are shown in Fig. 1.

As shown in Fig. 1, the upper left corner is the motion blurred image, the lower left corner is the Gauss noise, and the lower right corner is the Gauss noise + motion blurred image. From Fig. 1, we can see that when the original image is added with noise and motion blurred, the image quality decreases significantly. Compared with the original image, the PSNR values of the image with noise and motion blur are 26.9 and 25.9 respectively. From the PSNR values, the PSNR values of the image with Gaussian noise and motion blur are slightly smaller than that of the image with motion blur. The reason for this is that the introduction of Gaussian noise reduces the image quality. Similarly, for the parameter ssim, the similarity between the image with motion blur and the original image is 0.83, while the similarity between the image with Gaussian noise and motion blur and the original image is 0.71. From the noise analysis, it can be seen that the image distortion after adding noise is higher.

When the image is noisy, it needs to be de-noised. Fig. 2 shows the de-noising effect of the image after adding noise motion blur and Gaussian noise. Fig. 2 shows the de-noising effect of adding noise and motion blur to the left and de-noising result to the right. From the image, the Gaussian noise is obviously removed from the right image. The similarity of the two images is 0.92, while the PSNR value is 20.7, which indicates that the interference of Gauss noise has been removed obviously after denoising under high signal-to-noise ratio.

When using BP neural network algorithm for image restoration, because a simple three-layer BP neural network can approximate any non-linear continuous function with pre-set accuracy, this advantage is highly consistent with the theory of image restoration. Moreover, this method can adjust the threshold weights directly by training and learning without knowing the degradation of the image, so as to approach the degraded image to be restored as close as possible by iteration. In order to verify the feasibility of this method, this paper takes the real scene image as the background to simulate. Fig. 3 shows the simulation results. In Fig. 3, the original color image (upper left), the color image of the blurred scene taken in the same scene (middle), the result image restored (upper right), the gray result of the original image (lower right) and the gray image of the blurred scene are shown separately. From the comparison of the images, this paper uses BP neural network method to achieve image restoration very well. 。 Comparing different methods of image restoration, as shown in Fig. 4, using the classical blind convolution method and the method in this paper to restore the blurred scene, the left is the gray level of the original image, the middle is the blind convolution method, and the right is the method in this paper.

Fig. 2. Motion blurring denoising effect.

From the comparison results of Fig. 4, we can see that among the traditional image restoration algorithms, blind convolution algorithm is efficient, simple and reliable, and the restored image is better than the original image, but there is still a big gap compared with the method used in this paper.

Fig. 5 shows the comparison of PSNR and SSIM parameters between the two methods. From the comparison parameters, the difference of PSNR between the two methods is not significant, but the difference of SSIM parameters representing image similarity is large. The similarity between the original image and the classical

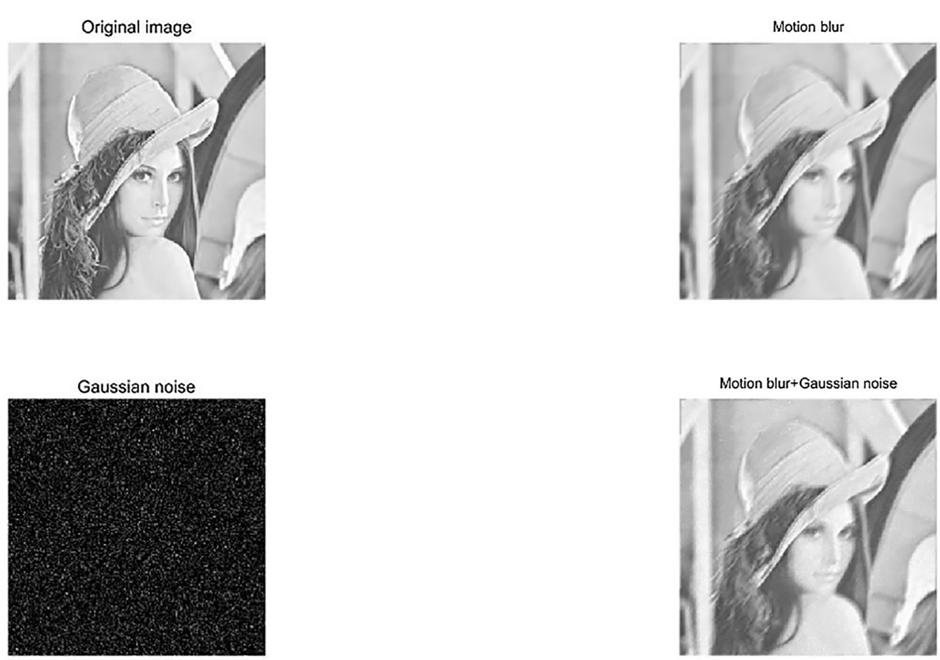

Fig. 1. Original image and noise processing image.

Fig. 3. Simulation results of realistic scenarios.

Fig. 4. Comparison of different methods.

method is only 0.35. However, the similarity of the BP neural network method used in this paper is 0.85. The results show that the method in this paper has greatly improved the image restoration.

5. Conclusion

By comparing the research and experimental results of traditional image restoration algorithm and BP neural network image restoration algorithm, it can be found that after motion blurring of the original image, the motion blurred image can dimly see the original image. This is because the image quality of the original image is relatively high and the resolution is high, so the effect of motion blur is not particularly obvious. After adding random noise to the motion blurred image, it is found that the effect of image restoration is not very good even if the mature inverse filtering restoration algorithm or Wiener filtering restoration algorithm is used. When using BP neural network algorithm to restore the image, we can see from the experiment that after blurring the original image and adding

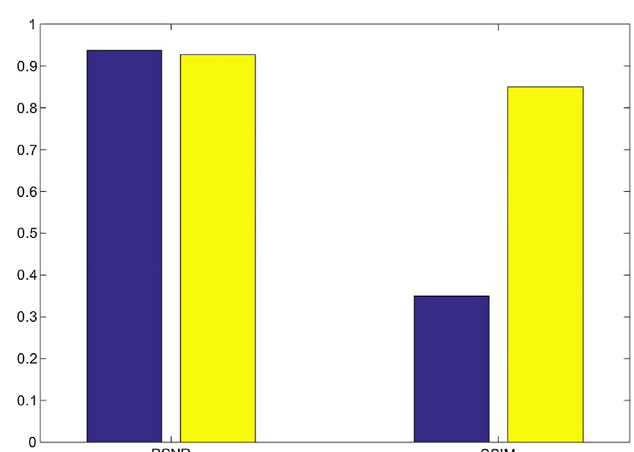

Fig. 5. Comparison of two parameters.

noise randomly, the BP neural network algorithm achieves better visual effect. This is because the image quality of BP neural network has been improved after many times of fitting. Traditional image processing methods have obvious ringing phenomenon and blurred image details. After using BP neural network algorithm, the effect of image restoration is obvious, the image appears smoother, and the noise is reduced. At the same time, the ringing phenomenon is restrained, the details and edges of the image are improved, and the image quality has been greatly improved.

Conflict of interest

There is no conflict of interest.

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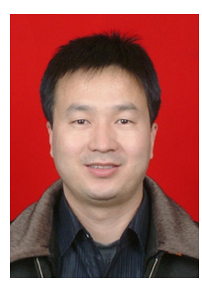

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