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Application of Improved Neural Network Algorithm in Image Denoising and Edge Detection

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Abstract

The knowledge involved in digital image processing is very wide, and there are many kinds of methods. Traditional image processing technology is mainly focused on the acquisition, transformation, enhancement, restoration, compression encoding, segmentation, edge extraction and so on. With the emergence of new tools and new methods, the image processing technology has been updated and developed. In this paper, an effective method for edge detection and image de-noising is proposed. In this article, the impulse noise detector is composed of a BP neural network (BPNN) and a decision switch. BPNN requires four input values, which are the current pixel value, grey median value, energy value, and contrast. To take these four values as the input values, the impulse noise detector can show good performance. The output of the BPNN is transferred to the decision switch, and the output value is converted to 0 or 1, which is used to distinguish whether the pixels are polluted. At this point, we introduce an additional impulse term and establish the improved BPNN model. The additional impulse term can effectively speed up the convergence of the network, avoid the emergence of the local minimum problem, and ensure the stability of the training process. In this way, the IBPNN filter of this paper only uses the information of the non polluted pixels to filter the noise pixels, which avoids the secondary pollution, and obtains a better performance. This algorithm has high PSNR value and strong detail information and edge preserving ability. Finally, the improved BPNN algorithm is applied to the image edge detection, and we use the improved neural network model to detect the edge of the image. Because the method can be used to include the prior knowledge, the IBPNN method is better than the traditional method in image edge detection.

***Keywords**: image processing technology, image de-noising, image edge detection, BPNN*

1. Introduction

The knowledge involved in digital image processing is very wide, and there are many kinds of methods. Traditional image processing technology is mainly focused on the acquisition, transformation, enhancement, restoration, compression encoding, segmentation, edge extraction and so on. With the emergence of new tools and new methods, the image processing technology has been updated and developed. To a certain extent, these image processing techniques reflect the intellectual activities of human beings. They use computer

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to imitate, extend and expand the human intelligence, and they have intelligent processing function.

Image de-noising is a key part of image preprocessing, and it is one of the important methods to analyze and understand the image. According to the characteristics of the image, the statistical characteristics of noise and the law of the spectrum distribution, the domestic and foreign scholars have put forward a variety of de-noising methods. According to the characteristics of the fuzzy mathematics theory and the random pulse noise, the paper [1] proposes the concept of the fuzzy index, combines the edge information, and proposes an adaptive median filtering algorithm. In the literature [2], the mean filter algorithm is improved by using the fuzzy weighting method. In the literature [3], an algorithm is proposed to remove the maximum and minimum pixels in the filter window, and then the adaptive filtering algorithm is proposed. An adaptive weighted median filtering algorithm is proposed in the literature [4]. A hybrid filtering algorithm is proposed which uses the local threshold to distinguish the pixels which are affected by Gauss noise and impulse noise pollution. In this article, the Gauss noise is filtered by the mean filter, and the median filter is used for the impulse noise [5]. Edge detection technology is another important technology in image feature extraction, and it is also the basis of image segmentation, target area identification, region shape extraction and so on. Image edge detection technology is widely used in various fields, such as military, medical, agriculture, meteorology and other fields. There are some traditional classical image edge detection operators, which are Roberts edge detection operator, Sobel edge detection operator, Prewitt edge detection operator, Kirsch edge detection operator, log edge detection operator and Canny edge detection operator. Although these operators are very simple and convenient, they can only be used to detect the a few types of edges. Therefore, their adaptability is poor. There are many methods in the field of image edge detection, such as canny theory and method [6-7], theory of mathematical morphology [8-11], multi-scale resolution theory [12-14], linear theory [15-16], fuzzy mathematical theory and method [17-18], classification theory [19], gradient theory [20,21], adaptive method [22], wavelet theory and method [23-25], Hilbert theory [26], *etc*.

In this article, the impulse noise detector is composed of a BP neural network (BPNN) and a decision switch. BPNN requires four input values, which are the current pixel value, grey median value, energy value, and contrast. The output of the BPNN is transferred to the decision switch, and the output value is converted to 0 or 1, which is used to distinguish whether the pixels are polluted. At this point, we introduce an additional impulse term and establish the improved BPNN model. The additional impulse term can effectively speed up the convergence of the network, avoid the emergence of the local minimum problem, and ensure the stability of the training process. The algorithm has high PSNR value and strong detail information and edge preserving ability. In addition, the improved BPNN algorithm is applied to the image edge detection, and we use the improved neural network model to detect the edge of the image. Because the method can be used to include the prior knowledge, the IBPNN method is better than the traditional method in image edge detection.

2. Neural Network Model

BP network is a feedforward network of multilayer structure, we mainly introduced the three layer of the BP network, that is, the input layer, hidden layer and output layer. All layers are connected between each layer, and the neurons are not connected in the same layer. Figure 1 shows the BP neural network structure with a hidden layer, the node number of the input layer and output layer is determined by actual situation, and the node number of hidden layer is calculated by the following formula.

There are many kinds of the activation function of the neurons in hidden layer, such as a step function, quasi linear function, sigmoid function and hyperbolic function; typical excitation functions are as follows:

$$F(x) = \frac{1}{1 + e^{-2x/u_0}} \tag{1}$$

Derivative function:

$$f'(x) = \frac{2}{u_0} f(x)(1 - f(x)) \tag{2}$$

Error function:

$$E = \frac{1}{2}\sum_{k=1}^{N} (Q_k - Y_k)^2 \tag{3}$$

Next, we give a topological map of the neural network model.

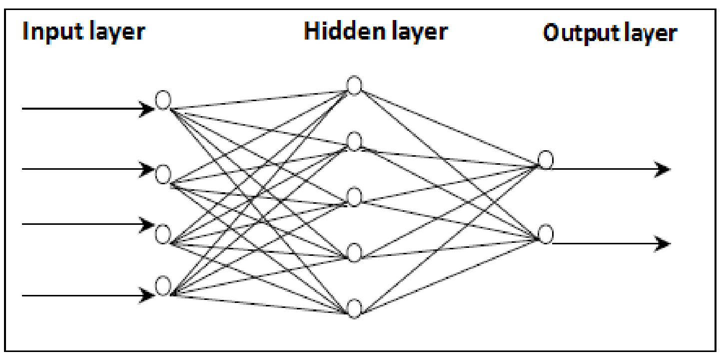

Figure 1. Topology of the BP Neural Network

3. Impulse Noise Detector

When the detector detects a noise pixel, the filter only filters the specific noise pixels. Noise model is given by formula 4.

$$I'(n) = \begin{cases} I(n), & 1 - p \\ G(n), & p \end{cases} \tag{4}$$

Where, $I(n)$ is the original non polluting image, $G(n)$ is a fixed value impulse noise, $I'(n)$ is a polluted image, p is the probability of being contaminated by noise, and n is a vector, that is, the coordinates (i, j) of the image pixels. In this article, the impulse noise detector is composed of a BP neural network(BPNN) and a decision switch. BPNN requires four input values, which are the current pixel value, grey median value, energy value, and contrast. To take these four values as the input values, the impulse noise detector can show good performance. The output of the BPNN is transferred to the decision switch, and the output value is converted to 0 or 1, which is used to distinguish whether the pixels are polluted. Next, we introduce the input values of neural network.

3.1. Input Values of Neural Network

Firstly, we make any pixel (i, j) as the center, determine the region which is $M * N$, and get the grey median value $M(i, j)$ of this region. Secondly, let $I(i, j)$ be the gray value of the pixel at (i, j), and calculate the weight value ω of all pixels within the $M * N$ region. The calculation method of the weight value is as follows.

$$\omega(i, j) = \frac{\dfrac{1}{1 + [I(i, j) - M(i, j)]^2}}{\sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \dfrac{1}{1 + [I(i, j) - M(i, j)]^2}} \tag{5}$$

The greater the difference between $I(i, j)$ and $M(i, j)$, the greater the weight given to it, and vice versa. All the pixels in the $M * N$ region are weighted sum by their weights, and the calculated value is the result of the median filter processing. Then, take this value as the first input value of the BPNN. Next, we take the image's energy and contrast as the second and third input value of the BPNN.

The meaning of energy is the sum of the squares of all the elements in the gray matrix, and the energy value of the image can reflect whether the gray distribution is uniform or not. The energy can be calculated by the following formula:

$$Energy = \sum \sum p(i, j)^2 \tag{6}$$

Where, $i, j \in [0, L-1]$ are the gray level of samples, and $p(i, j)$ is the existence probability of each gray value.

The meaning of contrast is the moment of inertia, which is located in the diagonal of the matrix. The contrast of the image can reflect the local change of the gray level, that is, the concave and convex of the texture of the image. The contrast is calculated by the following formula:

$$CON = \sum \sum (i - j)^2 p(i, j) \tag{7}$$

3. 2. Improved BPNN and its Modeling Process

Next, we give an improved BPNN training process and its step graph.

Step1: Initialization. Assign random values to all the weights, and set an initial value to the threshold value. The initial weights are random numbers between -1 and 1.

Step2: In the training data set, random select a model which includes the input vector x_k and expected output value y_k;

Step3: To calculate the input of hidden layer $s_j = \sum_{i=1}^{n} \omega_{ij} x_i^k - \theta_j$. Where, ω_{ij} and θ_j are respectively the hidden layer weights and threshold. Then, according to the formula 1, we can find out the hidden layer output is $b_j^k = f(s_j) = \dfrac{1}{1 + e^{-2 s_j / u_0}}$. Where, $i = 1, 2, \cdots, n$, $j = 1, 2, \cdots, m$.

Step4: To calculate the input of each unit of the output layer $l_t^k = \sum_{j=1}^{m} v_{jt} b_j^k - \gamma_t$ .Where, v_{jt} and γ_t are respectively the hidden layer weights and threshold. According to the formula 1 and step 3, we can find out the unit output value c_t^k

Step5: Calculates the error $e_j^k = f^{'}(s_j)\sum_{t=1}^{q} v_{jt} d_t^k$ of each unit in the hidden layer.

Step6: Modified the weights and thresholds $v_{ij}, \gamma_{jt}, \omega_{ij}, \theta_j$. Among them, η is the learning rate which is between 0.8 and 0.01,

$$\omega_{ij}(N+1) = \omega_{ij}(N) - \eta \frac{\partial E_k}{\partial \omega_{ij}(N)} \tag{8}$$

At this point, we introduce an additional impulse term. The additional impulse term is to add a term that is proportional to the change of the last time in the weight and threshold value of the network. The additional impulse term can effectively speed up the convergence of the network, avoid the emergence of the local minimum problem, and ensure the stability of the training process. Its calculation procedure is as follows.

$$\omega_{ij}(N+1) = \rho\omega_{ij}(N) - (1-\rho)\eta h_{\omega}(N) \tag{9}$$

$$\theta_{ij}(N+1) = \rho\theta_{ij}(N) - (1-\rho)\eta h_{\theta}(N) \tag{10}$$

Where, $\omega_{ij}(N)$ and $\omega_{ij}(N+1)$ are the current and modified weights; $\theta_{ij}(N)$ and $\theta_{ij}(N+1)$ are the current and the modified threshold; η is the learning rate; $h_{\omega}(N)$ and $h_{\theta}(N)$ are gradient of the weights and thresholds; and ρ ($0 < \rho < 1$) is the momentum factor.

Step7: Randomly select the next training mode, and provide it to the network. Then, return to the step 3 until each model has been trained.

Step8: According to formula 3, calculate the cumulative error E . If $E < \varepsilon$, the network learning ends, and the network convergence. Otherwise, return to the second step 2, and start the training again.

In this paper, the improved BPNN algorithm is a kind of neural network with three layers structure, which is composed of an input layer, a number of hidden layers and an output layer. The input layer is composed of four input nodes, which are the current pixel value, the gray median value, the energy value and the contrast. The hidden layer number of hidden layer is determined by the minimum fitting error. The output layer has only one output node. The output value is transferred to decision switch which is used to distinguish whether the pixels are polluted. Next, we give the flow chart of the algorithm in this paper.

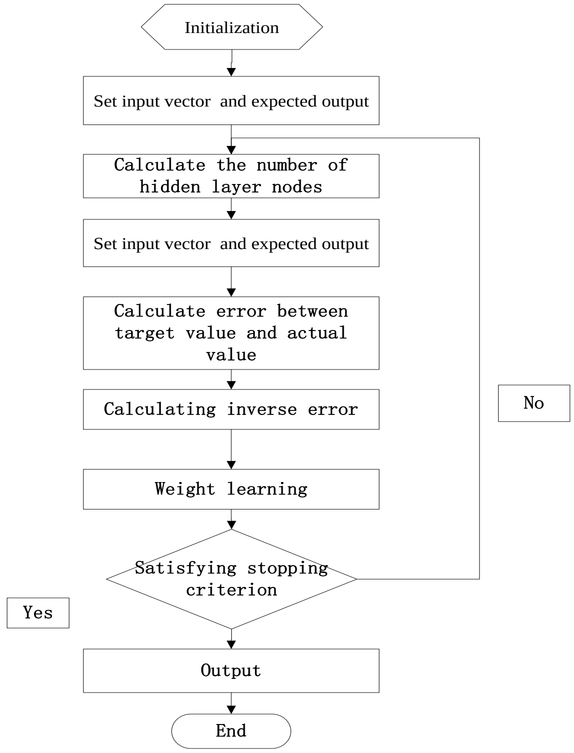

Figure 2. Flow Chart of the IBPNN

4. The Simulation and Result Analysis

Experiment A: Image de-noising.

Step1: first of all, we calculate the grey median value, the energy and the contrast of the graph 3, and take them as the input of IBPNN. Each pixel value is an 8 bit gray value which is between 0 and 255, and each input is normalized to $[0,1]$.

Figure 3. Original Image of Lena

Then, we train the IBPNN model. After many tests, the system has a minimum of fitting residuals when the nodes number of hidden layers is 3. Therefore, this paper is an IBPNN 4-3-1 model. Training results are shown in Figure 4.

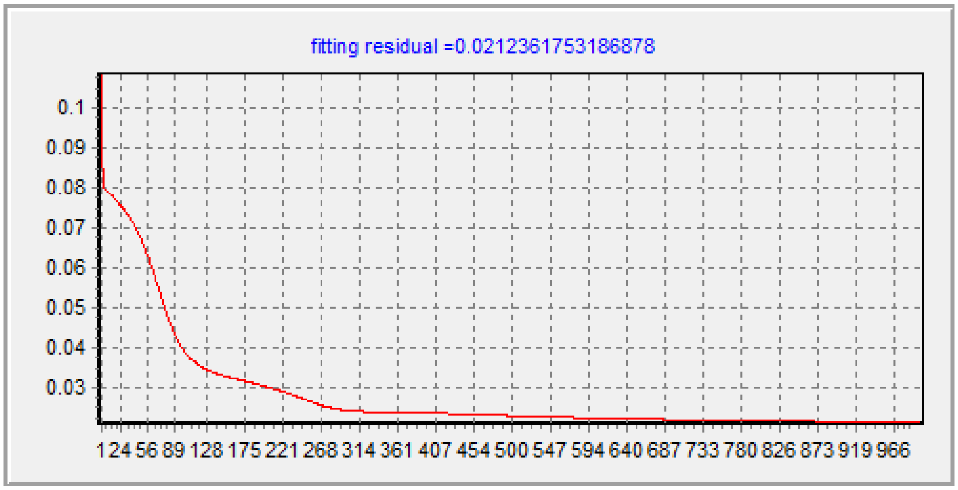

Figure 4. The Number of Hidden Layer Nodes is 3 in Neural Network Training (N=1000)

Next, this paper uses the Gauss filter, median filter and IBPNN filter to test the Lena image that containing 30% noise pollution, the experimental results are shown in Figure 5-7:

Figure 5. Gauss Filter

Figure 6. Median Filter

Figure 7. IBPNN Filter

Step2: In order to quantitatively evaluate the performance of various algorithms, we use mean square error (MSE), normalized mean square error (NMSE) and peak signal to noise ratio (PSNR) as the comprehensive evaluation index of filtering performance. Among them, the PSNR value is the average value of running 10 times. Table 1 is the comparison results of quantitative performance of the standard median filter (SMF), Gauss filter (GF), and IBPNN filtering.

Among them, the mean square error (MSE), normalized mean square error (NMSE) and peak signal to noise ratio (PSNR) calculation method as shown in formula 11-13.

$$PSNR = 10\log_{10}\frac{255^2}{\frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}(I(i,j),I^{'}(i,j))^2} \tag{11}$$

$$MSE = \frac{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left\| I(i,j), I^{'}(i,j)\right\|^2}{3mn} \tag{12}$$

$$NMSE = \frac{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left\| I(i,j), I^{'}(i,j)\right\|^2}{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left\| I(i,j)\right\|^2} \tag{13}$$

Where, $I^{'}(i,j)$ and $I(i,j)$ are gray values of the noise image and the original image at the point (i,j) , m and n are the number of rows and columns of the image.

Table 1. The Average PSNR Value of Each Algorithm

	PSNR(dB)	MSE	NMSE(10^{-4})
MF	28.55	6.99	24.45
GS	30.26	6.75	23.18
IBPNN	37.59	3.35	11.19

The experimental results show that the Gauss filter can remove some noise, but it also causes the image blur, and the image detail information is lost. Although the median filter can avoid blurring the image, it will lose the details such as the corners and lines. As we all know, it is usually only a few pixels affected by the noise in the image, while the remaining pixels remain the original value. Therefore, filtering all pixels without selecting will inevitably lose some of the original information of image. The filtering method proposed in this paper is added the judgment to the filter processing. It can switch the output result between original pixel gray values and filter results, so as to get a better image de-noising effect.

Experiment B: Image edge detection.

First of all, Lena image is edge processed by us, and then we get the Figure 8. After that, we use the Roberts operator and the Sobel operator to detect the image edge in Figure 8, and then we get the Figure 9 and Figure 10. At last, we take the detection effect of the two algorithms and the weighted average of pixel gray level as the training image of the IBPNN method. At this point, the input layer of the neural network is 3, the hidden layer is 3, and the output layer is 1.

Figure 8. Original Edge Image

Figure 9. Edge Detection Results of Roberts Operator

Figure 10. Edge Detection Results of Sobel Operator Sobel

Figure 11. Edge Detection Results of our Method

In Figure 9, the experimental results show that the edge detection of Roberts operator has a large edge fracture. Then, the detection effect of the Sobel method is not good in figure 10. In this paper, the IBPNN algorithm using adaptive learning rate, saving the network learning time, making the network training efficiency has been improved. As can be known from figure 11, it has a very good edge connection, and the contrast of edge and non edge is obvious, so it is the best test results. At the same time, it is one of the reasons for the better detection results that we carried out the image de-noising before edge detection. Therefore, the IBPNN algorithm which is proposed in this paper has better image detection effect than the other two algorithms.

5. Conclusion

In this article, the impulse noise detector is composed of a BP neural network (BPNN) and a decision switch. BPNN requires four input values, which are the current pixel value, grey median value, energy value, and contrast. The output of the BPNN is transferred to the decision switch, and the output value is converted to 0 or 1, which is used to distinguish whether the pixels are polluted. At this point, we introduce an additional impulse term and establish the improved BPNN model. The additional impulse term can effectively speed up the convergence of the network, avoid the emergence of the local minimum problem, and ensure the stability of the training process. The algorithm has high PSNR value and strong detail information and edge preserving ability. In addition, the improved BPNN algorithm is applied to the image edge detection, and we use the improved neural network model to detect the edge of the image. Because the method can be used to include the prior knowledge, the IBPNN method is better than the traditional method in image edge detection.

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