Enhancement of Degraded Image Based on Neural Network

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Abstract
Inevitably, image degradation is caused in the imaging, reproduction, scanning, transmission and display. This paper conducts systematic analysis and research on the clearness processing of degraded image based on BP neural network. The proposed scheme increases the output ranges of the hidden layer and the output layer, sets the variable step size, accelerates the learning speed of the neural network and avoids the excessive correction of the weights and speeds up the convergence rate of the neural network. It can preserve more profound image information, greatly enhance the contrast of the degraded image, effectively strengthen the overall quality of the degraded image and obtain more ideal image clearness effect while processing the degraded image acquired under bad conditions.
Key words: IMAGE CLEARNESS, BP NEURAL NETWORK, DEGRADED IMAGE

1. Introduction

The image we record usually has certain degree of degradation, including some pixel displacement, object distortion and distance ratio imbalance in the image due to the imperfect actual imaging system, the impact of transmission media, the relative motion between the scenery and the imaging system and the random environment noises in the formation, transmission and recording of the image[1]. In fact, this is the so-called image degradation. The purpose of image clearness restoration processing is to process the degraded image to restore it into the original image and this is the foundation of image processing, pattern recognition and machine vision[2].

The traditional image clearness restoration is faced with the computation of high-dimensional equations, which has a heavy computation load, requires the assumption to satisfy the generalized stationary process in the restoration or lacks complete theoretical foundation and unified design method[3]. This is the fundamental reason why the image restoration problem with extensive application value can’t be solved satisfactorily. Neural network has certain advantages in the restoration of image clearness because the image clearness based on neural network doesn't need to assume that the image meets the wide-sense stationary process and that it is easy to realise[4]. By analyzing the features of degraded image and having a great number of trainings, neural network method can accurately identify and extract the fuzzy regions in the locally-moved fuzzy image, search the fuzzy features in the image, set the parameters, process the fuzzy regions and get the restored image in the complicated backgrounds and unclear gray features[5].

Firstly, this paper designs the hidden layer, the output layer and the step size of BP neural network in accordance with the clearness restoration of degraded image. Secondly, it gives the basic procedures of the algorithm in this paper and the steps of the restoration of image clearness. Finally, it is the experiment simulation and analysis.

2. BPAlgorithm

BP neural network algorithm is a back-propagation algorithm, the operating base of which is multi-layer feed-forward neural network. Ever since it was proposed in the 1980s, it has been attracting increasing attention, so far, it has been widely applied in various forefront fields.

2.1. Introduction of BP Algorithm

As one of the layered network models, BP neural network model includes input layer, output layer and multiple hidden layers. Besides, there are several units in every layer of BP neural network model and the connection between the units is realized by directed weighted edge. Attention shall be paid to several problems here:

1) The network is feed-forward and single, that is to say, every feedback can only be sent to the front neighborhood output layer or hidden layer but not to span and propagate backwards.

2) The network is fully connected. In other words, it is in a one-to-many relationship, namely that the units in every layer are connected with all units in the previous layer through directed weighted edge.

Therefore, as long as there are enough hidden layers in the middle, the linear threshold function in the multi-layer feed-forward neural network can approach any function sufficiently. Besides, before the neural network training starts, the structure of the neural network must be confirmed, namely the following shall be confirmed: the units in the input layer, the number of hidden layers, the units of every hidden layer and the units of the output layer. However, there isn't a specific theoretical basis for us to follow as for how to confirm the number of nodes in every hidden layer and the number of network layers [6].

2.2. Process of BP Algorithm

In the above discussion, it has been confirmed BP neural network model is one of the multi-layer feed-forward neural network models.Its structural pattern must be confirmed before utilizing BP neural network model (it is certain that such structure may change after that. Then divide the original data provided, including training data, test data and inspection data. In the calculation, obtain the calculation error between the data and that of the node in the forward layer and adjust its weight and threshold so that the input data and output data satisfy certain mapping relationship given before[7].

It can be seen that by principle, BP neural network model can be divided into three parts.

Forward propagation input:

Calculate the net input of the unit $I_j = \sum_I w_{ij} o_i + \theta_j$ and the data to be used is the bias between the linear combination and unit. Use activation function activation function in the net input of the unit and get the unit output $O_j = \dfrac{1}{1+e^{-I}}$.

Calculate the error

Error calculation reflects the network prediction error through the weight updates and the bias and back propagate the predicted error. Calculate the error E_{rrj} of the unit j in the output layer with the following formula:

$$E_{rrj} = O_j(1-O_j)(T_j - O_j) \tag{1}$$

Update the weight and bias

The update methods include instance update and periodic update. The former update of weight and bias are made after processing a data. In this way, it has excellent timeliness but its parallel processing capacity is not so strong and that is why periodic update comes into being. The basic idea of periodic update is to update the weight and bias after processing trained and centralized samples. There are three termination conditions: the first is that the variation of all w_{ij} in the previous period is smaller than a certain given threshold, the second is that the percentage of the samples which are not correctly classified in the previous period is smaller than a certain threshold and the third is that it has exceeded the pre-assigned number of periods[8].

2.3 Standard Formula of BP Algorithm

It is inevitable to discuss the input and output of the nodes in the BP neural network model.There are no specific conclusions to follow in the existing academic materials in the selection of the initial neural network parameters such as the weight w, the deviation value θ and the learning rate i of that network model[9].

The input and output calculation formula

(1) The value of the input node in the input layer: x_j

(2) The output of the hidden node in the hidden layer: $y_i = f(\sum_i w_{ij} x_j - \theta_i)$

(3) The output of the output node in the output layer: $o_i = f(\sum_i T_{ij} - \theta_i)$

The modified formula of the output layer

(1) The expected output of the output node: t_i

(2) Error control: $E = \sum_{k=1}^{p} e_k < \xi_r$

(3) Error calculation: $E_{rrj} = o_j(1-o_j)(T_j - o_j)$

(4) Weight modification: $T_{ij}(k+1) = T_{ij}(k) + lE_{rrj} o_i$

(5) Threshold modification: $\theta_{ij}(k+1) = \theta_{ij}(k) + lE_{rrj} o_i$

The modified formula of the hidden layer

(1) Error calculation: $E_{rrj} = o_j(1-o_j)\sum_k E_{rrk} w_{kj}$

(2) Weight modification: $w_{ij}(k+1) = w_{ij}(k) + lE_{rrj} o_i$

(3) Threshold modification: $\theta_{ij}(k+1) = \theta_{ij}(k) + lE_{rrj} o_i$

3. Establishment of BP Neural Network

3.1 Design of Transfer Function

Transfer function is an important part of BP network and we usually use S-type logarithmic or tangent function. Before the input, make a quantized unification on the original data to make the input vectors within the range of [-1,1] and meet the value requirements of the above transfer functions. Therefore, this paper selects $\tan sig$ and logsig as the transfer functions of the hidden layer and the output layer respectively [10].

$\tan sig$ is a hyperbolic tangent S-type transfer function with its graph as indicated by Fig.1.

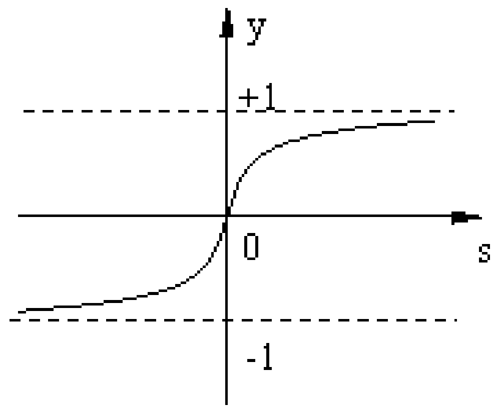


Figure 1. Hyperbolic tangent s-type transfer function

logsig is the S-type logarithmic function and its call format is:

$A = \log sig(N)$

$\text{info} = \log sig(\text{code})$

In here, N is S-dimensional input vectors and A is the function return value within the range of (0,1).

$\text{info} = \log sig(\text{code})$ returns different information according to the differences of code value.

See its function graph as Fig.2.

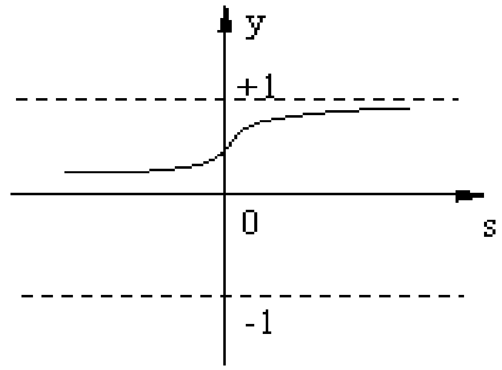


Figure 2. S-type logarithmic function

3.2.Design of Initial Weight

Initial weight is of great significant in the neural network because it determines the initial state of the error. Normally, the smaller the design of the initial weight, the better since in this way every neuron in the neural network can be close to uniform distribution in that layer.

This paperhas few requirements on the parallel capacity and error analysis of BP neural network, however, since the prediction result is based on short-term trend, it has higher accuracy requirements.

This paper uses Function init provided by Matlab. An initial value randomly generates among [-1,1]. It uses the characteristics of BP neural network in the entire process, adjusts its numerical value by calculating the error and finalizes the numerical value of initial weight[11].

3.3 Design of Training Function

The data collected in this paper are all within the range of [0,1] after normalization processing and the differences between every numerical values are small, therefore, the training function this paper selects is traindx. In accordance with the time, number and accuracy requirements on the training data, this paper defines the times of training as 20000 and sets the training target error and learning rate as 0.001 and 0.01 respectively. See the details as followsin Fig.3:

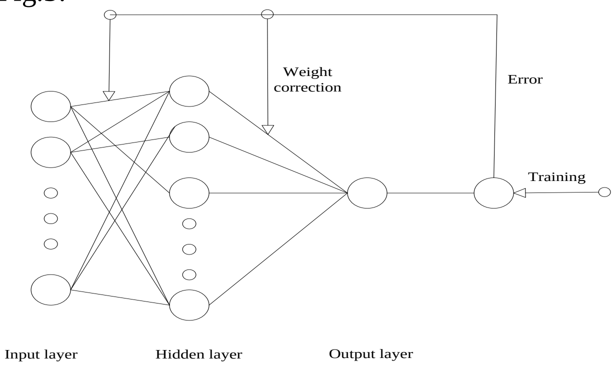


Figure 3. Training process of BP network

3.4 Design of Performance Function

In its research, in order to make the model universal and applicable, it improves its generalization ability on new samples to reduce training error.

The feed-forward network error performance functions used in this paper are Mean Square Error mse:

$$F = mse = \frac{1}{N}\sum_{i=1}^{N} e_i^{\,2} = \frac{1}{N}\sum_{i=a}^{N}(t_i - a_i)^2 \qquad (2)$$

Although there is another performance function, which is the modifying network error performance function msereg, namely:

$$msereg = r * mse + (1-r)msw \qquad (3)$$

In here, r is the error performance adjustment ratio and $msw = \frac{1}{n}\sum_{j=1}^{n} x_j^2$.

The above has form the complete design and study process of a complete BP neural network model[12].

4. The Flow and Steps of BP Neural Network Algorithm

The image clearness based on BP neural network algorithm includes the following steps:

(1) Read the image, obtain its pixel matrix, extract the gray value of every pixel point, computes the membership of pixel (m,n) in the matrix by using the membership function and set the input vector P and the target vector.

(2) Initialize BP neural network and set the learning rate $\eta(0)$ of the first sample training. The training lasts from the input of the samples till the network error reaches the set value or the maximum number of trainings has reached and preserve the weight and threshold.

(3) Read in the image to be processed. The image to be adopted here is the 128×128 football image with a gray scale of 256. Degrade the original image through 5×5 function and its form is:

$$H = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 8 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} / 32 \qquad (4)$$

(4) Define the range of the gray value of the degraded image Y within [− 0.5,0.5], i.e. the value range of every neuron x_i is within [-0.5, 0.5], so as to reduce the error which is introduced when forcing x_i of every iteration into the value range to certain extent: $Y = \frac{Y}{255} - 0.5$, the initial value $x(0) = H^T Y$, $t = 0$ and the admissible error of the network convergence is $err = 10^{-5}$.

(5) Select the image to be sharpened, train the input vector with the well-trained BP neural network. And the final output vector is the restoration processing result of the image.

(6) Restore the image restoration result into the image grayscale matrix in the form of vector and display the result.

The key flow othe improved method is indicated in Fig.4:

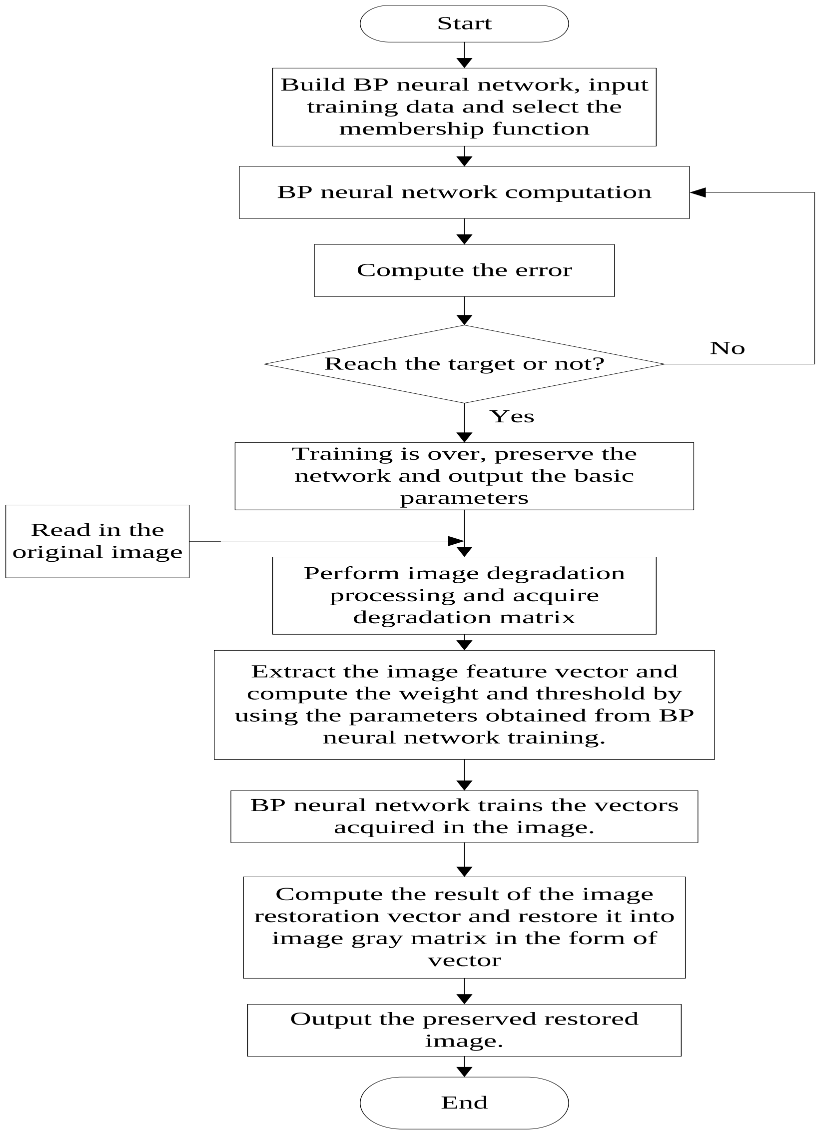


Figure 4. The main flow of improved method

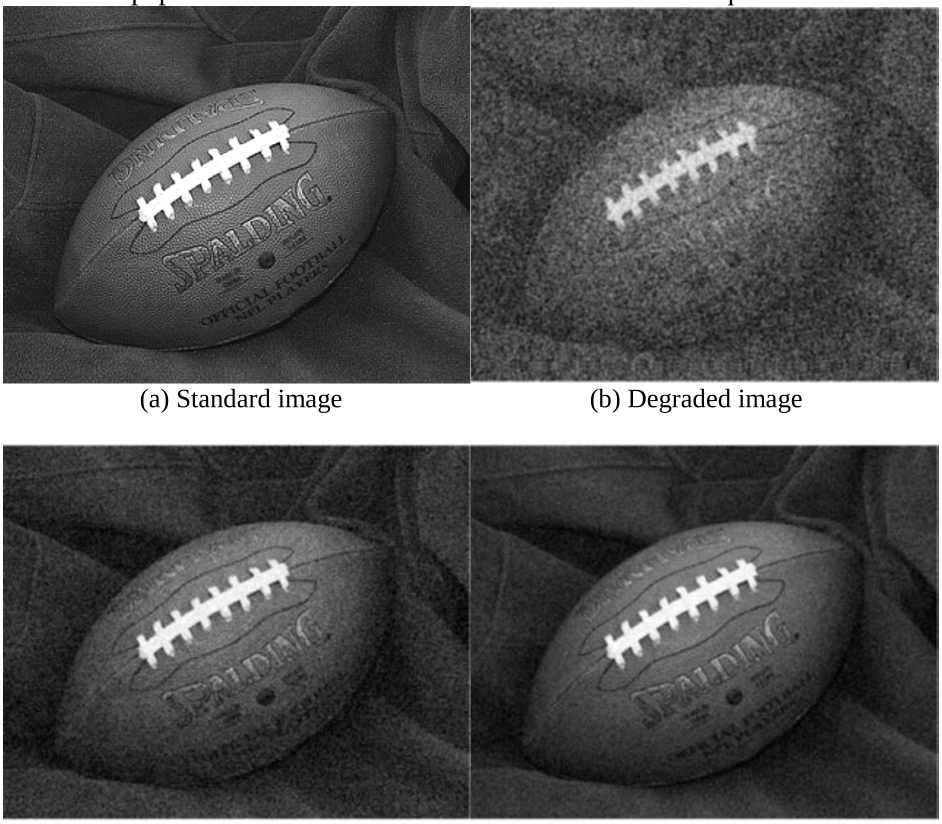
The selection of the learning rate η is very important. If η is too big, the weighted coefficient may not be converged because of repeated vibration, if η is too small, the learning rate can be relatively slow, causing too much time in network convergence, therefore, the inertia coefficient αis usually introduced to accelerate the network convergence when η is small and to assist in the network convergence when η is big[13,14].

Another problem of BP network is that the system may be trapped into certain local minimum, or certain quiescent point or vibration among these points in the learning process. Under these circumstances, the system will have huge errors no matter how many iterations have been performed. Therefore, in the learning process, avoid the system to be trapped in certain local minimum points and the introduction of inertia item may avoid the network to be trapped in vertain local minimum[15].

5. Experiment Simulation and Analysis

The original clear image adopted in the simulation experiment is the 128x128 football image with a gray scale of 256. Fig.5(C) is the restoration result of the least square method and Fig.5 (D) is the restoration result of BP network.

It can be seen from the comparison of the above experiment results that BP neural network has greatly improved the quality of the restored image with well-preserved image details, comfortable sense of feeling to human eyes in the processed image and obvious effect. The method integrating $\tan sig$ function and $\log sig$ function has provided the network with stronger function approximation capability and the obvious improvements in the image restoration has proved that the method in this paper is better than the traditional least square method.



(a) Standard image (b) Degraded image

(c) Least square method (d) BP neural network

Figure 5. Comparison of restoration of image clearness

6. Conclusion

In various image systems, the image is usually degraded because of image transmission and conversion such as imaging, reproduction, scanning, transmission and display. In order to improve the image quality, this paper has investigated the clearness of degraded image based on BP neural network from the aspects like the transmission function, the network learning rate and the training algorithm of BP neural network. And the experiment simulation in the final part has verified the effectiveness of the method of this paper.

Acknowledgements

This work was supported by the Beijing Philosophical Social Science Project (No.14SHB015), the Beijing Municipal Education Commission Foundation of China (No. SM201410038013) and the National Natural Science Foundation of China (Grant No: 61202464).

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