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Face Recognition Algorithm Based on Improved BP Neural Network

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Abstract

Face recognition has received wide concern as a hot direction in recognition models. Due to a strong self-adaptive and mapping ability, traditional BP algorithm occupies certain advantages in face recognition, but is has the shortcomings of fast convergence speed and being easy to fall into local optimum in itself. In this paper, an improved BP neural network is proposed aiming at the deficiency of BP algorithm and obtaining features of face images through Gabor filter, and then reducing dimensions of vectors by the method of chaos algorithm and improved weight analysis. Simulation experiments show that improve algorithm in this paper has a relatively high recognition rate in face recognition.

Keywords: *BP neural network, chaos, Gabor, weight*

1. Introduction

Currently, face recognition has a quite high accuracy, but in practice, due to the influence of different factors like lighting conditions, expression photoreception and face postures, etc. collected face recognition contains a lot of noise. Besides, recognition rate of face recognition algorithm is sensitive to light, so it is a difficult problem to urgently needed to be solved to improve accuracy of face recognition in complex conditions [1, 2].

Scholars both an home and abroad have conducted a lot of researches on face recognition in lighting condition, and have adopted some algorithms for face lighting pretreatment so as to improve the quality of face images. The most traditional algorithm is to use several face images of the same scene to get the lighting information of the image scene and restore face images. The algorithm relatively complicated in computing, so it can hardly meet the real-time requirement of face recognition [2]. At present, image enhancement processing technology is mainly used to improve the quality of face images in complex lighting conditions, and improve the face image contrast, highlight detailed information and improve visual effects of the images from the perspective of image processing [3]. Classic light process processing algorithms include: linear transformation, nonlinear transformation and histogram equalization, [4-6] etc. These algorithms are simple and easy to implement, but there are big lighting changes, their enhancement effects are not obvious, thus they cannot meet the actual demands of face recognition [7]. In recent years, BP neural network algorithm has been introduced by some scholars to the enhancement and processing of face images, which has provided a new research idea for the problem of face recognition in lighting conditions. BP neural network algorithm is a multilayer feed-forward network trained according to the reverse transfer algorithm, and the most widely used neural network model at present. When data of face images have a

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relatively small scale, the operation of single BP neural network is relatively ideal, but when the complexity of face samples increases gradually, structure of BP network also becomes complex, resulting in long training time and slow convergence speed. Besides, it is easy to fall into local minimum with poor generalization ability.

In this paper, on the basis of the above research, features of face images are obtained by Gabor filter, and then dimensions of vectors are reduced by chaos algorithm and improved weight analysis method. Improved algorithm in this paper has a relatively higher rate of recognition.

2. Gabor Algorithm

Gabor can well capture prominent visual attributes, and especially, Gabor wavelet can extract features of multi-scale and multi-directional spatial frequency within a specific region of the image, and amplify gray changes like a microscope. Since Gabor features are extracted from local images, so it has a good robustness in convergence of face images and the reflection of face images. Two dimensional Gabor kernel function is defined as:

$$\psi_{\mu,v}(z)=\frac{\left\|k_{u,v}\right\|2}{\sigma^2}e^{-\frac{\left\|k_{u,v}\right\|2\left\|z\right\|2}{2\sigma^2}}\cdot\left(e^{ik_{\mu,v}\cdot z}-\mathrm{e}^{-\frac{\sigma^2}{2}}\right) \quad (1)$$

In the formula, σ defines the bandwidth of wavelet; is the complex operator; z=(x,y) stands for pixel coordinates; μ、v represents the direction and scale of wavelet. $k_v = k_{\max} / f^v$, herein, $k_{\max}$ represents the maximum frequency and f represents the interval factor. And $k_v = k_{\max} / f^v$ represent wave vector of wavelets.

Gabor feature extraction is completed through the convolution operation of the Gabor filters, which have v dimensions and μ directions, with the image respectively. Suppose $I(Z)$ is the pixel value of face image at the point z, and its convolution with the Gabor filter is defined as:

$$G_{\mu,v}(z)=\psi_{\mu,v}(z)*I(z) \quad (2)$$

In the formula, $G_{\mu,v}(z)$ is the filtering results of wavelet kernel function at the dimension μ direction port at the point z.

Then after the Gabor kernel convolution of each point $P(m,n)$ on the image, dimensional features of Gabor are quite high. If statistics are made to a 100×100 picture roughly according to the pixel gray, the features have 10000 dimensions, which are a relatively high dimension from this direction. If a 6-scale and 8-directional Gabor filter is used, then after the Gabor transformation, original features are increased to 6×8×10000=480000 dimensions, which is obvious. Feature vectors under such a high dimension are not appropriate to be used for face recognition. Therefore, in this case, it is necessary to adopt a suitable dimension reduction approach to reduce the facial features from a high-dimensional space to a low-dimensional space.

2.1 Gabor Coefficient Blocking Thinking

Because there are problems with original Gabor features like high dimension and redundancy, etc. face image regions are first partitioned in this paper so as to collect statistics of the average value and variances of Gabor coefficients of certain scales and directions in each sub-block. Then, these average values and variances are combined to form feature vectors in the means of scale first and direction next, and finally, in the sequence that line first and column next, these block feature vectors BFV are joined together to form feature vectors of face images. This not only effectively reduces the feature dimensions, but also makes full use of the statistical information of all the Gabor coefficients within the block. Its construction process is shown in Figure 1.

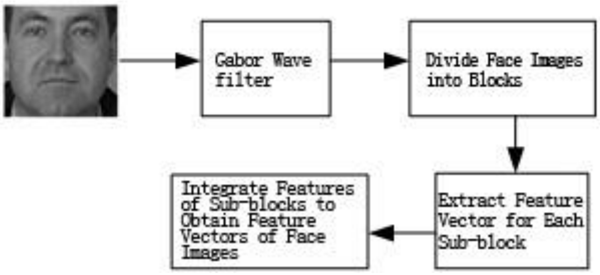

Figure 1. Diagram of Extracting Features Block by Block by Gabor Coefficient

2.2 Extract Features of Each Block

Divide face images into blocks according to a particular length and width to get the *Block* that to be processed. The number of all the points in this block is *N*, then steps to extract features of each block are:

(1) Collect the average value of *c* -scale and *f*-direction filtering results of all the points:

$$\overline{G}_{c,f} = \frac{1}{n}\sum_{t\in Block} G_{c,f}(t) \quad (3)$$

(2) Collect the standard deviations of *c* -scale and *f*-direction filtering results of all the points:

$$D_{c,f} = \sqrt{\frac{\sum_{t\in Block}(G_{c,f}(t)-\overline{G}_{c,f})^T(G_{c,f}(t)-\overline{G}_{c,f})}{N-1}} \quad (4)$$

(3) *Block*'s feature vector *BFV* can be signified with vector V_{Block}:

$$V_{Block} = (\|\overline{G}_{0,0}\|, \|\overline{G}_{0,1}\|, \cdots, \|\overline{G}_{4,7}\|, D_{0,0}, D_{0,1}, \cdots, D_{4,7}) \quad (5)$$

3. BP Neural Network

The BP neural network is a one-way transmission network composed of input layer, hidden layer and output layer. It delivers signals forward and transmits them in reverse. Herein, when the signals are transmitted in reverse, the weight is adjusted according to the Delta learning rule. In delivering forward, input and output of each layer are calculated according to formula (6) respectively until they have reached the output layer. When expected output cannot be obtained at the output layer, back transmission is carried out, and weight values and threshold values are adjusted according to the deviation between expected and actual output. Weight adjustment formula is shown in formula (7).

$$W_i = \sum_j w_{ij}x_j + \theta_i$$

$$y_i = f(W_i) \qquad (6)$$

In formula (6), W_i is the activation value of nodes at the layer i, θ_i is the threshold value, x_j is input signal, w_{ij} is connection weight coefficient of node i and j, y_i is the output value of node i .

$$w_{ij}(t+1) = w_{ij}(t) + \frac{\partial E}{\partial w_{ij}} \quad (7)$$

In formula (7), $\frac{\partial E}{\partial w_{ij}}$ is the deviation between expected output and actual output of neural network.

4. Gabor Face Recognition Algorithm Based on Improved BP Network

4.1 Improvement of BP Network Algorithm

Currently, gradient descent algorithm is mainly used in BP network. It has slow convergence speed in the learning process, and it vibrates in the training process and is easy to fall into local minimum. Based on this, a gradient descent adjustment method of weights is proposed in this paper, which improves BP neural network through the adjustment of weights, thus accelerating the convergence speed and precision of network.

(1) Chaotic Variables

Chaos algorithm is a novel optimization technique, which can reduce vibrations in terms of numerical optimization in the training process of face images, reflect solutions produced in the searching process into variable space through chaos, and find the optimal solution by using the ergodicity and randomness of chaotic variables so as to avoid falling into the minimum in the searching process and obtain the global optimal solution [8]. Since the chaos algorithm is random and bounded, many literatures use the improved algorithms of chaotic sequence [9-10]. In this paper, cub reflection in the chaotic sequence is used to prove that the reflected sequence is stronger than the current common logistic sequence. The expression is shown as follows:

$$\begin{aligned} & y(n+1,d) = y(n,d)^3 + 4y(n,d)^2 - 3y(n,d) \\ & -1 \le y(n,d) \le 1 \quad n = 0,1,2,........ \end{aligned} \qquad (8)$$

In formula (8), chaos optimization process is as follows: individual uses logic to reflect characteristics of functions and reflect the individual space to interval [-1, 1] according to formula (9)

$$L_{id} = 2 \cdot (y_{id} - d_{i\min}) / (d_{i\max} + d_{i\min}) \quad (9)$$

Integrate formula (8) and formula (9), new chaotic individual is got as the formulas are loaded into the individuals through chaotic variables, and new chaotic individuals are transformed according to formula (10). Herein, $d_{i\min}$ and $d_{i\max}$ represent the minimum and maximum value of face image i in the D dimensional space.

$$x'_{id} = (d_{i\max} - d_{i\min}) \cdot L_{id} + 1/2 \cdot (d_{i\max} - d_{i} \qquad (10)$$

(2) Improved Weight Adjustment

Weight has always not been considered in the adjustment process of traditional BP neural network, and instable weight is easy to cause a vibration. Because BP neural training takes too long time, if the elastic gradient descent method described before is adopted, it is say to lead to instability in identification. Set the weight as $W(t)$, $0 < \beta < \alpha < 1$. Therefore, it is needed to adjust it on the basis of formulas (11-13)

$$\Delta W(t) = \begin{cases} -\Delta t & \dfrac{\partial E(t)}{\partial W} > 0 \\ +\Delta t & \dfrac{\partial E(t)}{\partial W} < 0 \\ 0 & \dfrac{\partial E(t)}{\partial W} = 0 \end{cases} \qquad (11)$$

$$W(t+1) = W(t) + \Delta W(t) \quad (12)$$

$$\Delta t = \begin{cases} \alpha \times \Delta(t-1) & \frac{\partial E(t-1)}{\partial W} > 0 \\ \beta \times \Delta(t-1) & \frac{\partial E(t-1)}{\partial W} < 0 \\ \\ \Delta(t-1) & \frac{\partial E(t-1)}{\partial W} = 0 \end{cases} \quad (13)$$

On the basis of formula (11-13), a new neural network weight adjustment way is proposed in this paper, which is as shown in formula (14)

$$W(t+1) = \begin{cases} W(t) - \sin(\frac{\partial E(t)}{\partial W})\Delta t & \frac{\partial E(t)}{\partial W} > 0 \\ W(t) - tag(\frac{\partial E(t)}{\partial W})\Delta t & \frac{\partial E(t)}{\partial W} < 0 \\ 0 & \frac{\partial E(t)}{\partial W} = 0 \end{cases} \quad (14)$$

When continuous iterative gradients have the same direction, updated value of weight will also be adjusted accordingly, herein, mc refers to the momentum coefficient, which is as shown in formula (15)

$$\Delta t = \alpha \times (1 - mc) \times \Delta(t-1) + mc \times \Delta(t-1) \quad (15)$$

When the continuous iterative gradients are of the opposite directions, updated value will be smaller, and meanwhile weight will maintain the current direction with a certain probability, thus making individual have the chance to escape from local optima. Herein, mc refers to the momentum coefficient, and at this time, adjustment of Δt is as shown in formula (16):

$$\Delta t = \beta \times (1-\alpha) \times (1 - mc) \times \Delta(t-1) + mc \times \Delta(t-1) \quad （16）$$

Through the above updating and adjustment of weights, adverse effects of overcoming gradient magnitudes to the slow convergence speed caused by the network can be found. When sudden changes take place in network deviation, the possibility that network falls into local optimum can be effectively reduced so as to improve the network's recognition speed and efficiency.

4.2 Algorithm Steps

Firstly, in this paper, images in high-dimensional space are reflected into low-dimensional space through Gabor algorithm so as to extract main features of face images. And then BP network is improved by integrating chaos algorithm proposed in this paper and elastic gradient descent algorithm for feature training of main features of images in the face database, and the trained network is tested by testing images, the concrete steps are as follows:

Step 1: Read images in the face database, and select M sub-pictures for training. Images with the resolution $m \times n$ as are set to be connected to each other in the unit of column so as to form a $m \times n$ dimensional column vector. Therefore, the entire face image can be stored in the matrix $R^{m \times n}$, herein image i is stored in the i column of $R^{m \times n}$. Therefore, average face image used for training is $\bar{x} = \frac{\sum_{i=1}^{M} x_i}{M}$;

Step 2: Construct covariance matrix C for the building of difference of images for training and average value;

$$C=\frac{1}{M}\sum_{i=1}^{M}(x_i-\bar{x})A(x_i-\bar{x})^{T}A^{T} \quad (17)$$

Step 3: Solve featured subspace reflected by the images, and C is a $N \times N$ matrix. In order to simplify the computation of face image, solutions are got indirectly by solving the eigenvalues of matrix AA^T and eigenvectors. Firstly, arrange the λ in descending order according to eigenvalues of A^T, and set A^T as the first i eigenvalue ($i \le r$) of matrix A^T, and $v_i(i=1,2\ldots\ldots r)$ as the corresponding vector of the first r eigenvalue. By decomposition theorem, there comes follows:

$$\varepsilon_i=\frac{1}{\sqrt{\lambda_i}}AA^{T}v_i \quad (18)$$

Herein, ε_i is the solution in featured space AA^T.

Step 4: Project images for testing and average face images, and get the corresponding projection coefficient.

$$Y'=U^{T'}(x_i'-\bar{x}) \quad (19)$$

Step5: Normalize it after the projection in step 4, and train BP neural network with normalized Y' as the network input, herein, specific input amount at BP neural input layer is determined by projection coefficient Y'. Herein, the number of neurons in BP is determined according to experience and repeated testing.

Step 6: Use the projection coefficient of trained network to testing face images in featured subspace to determine the amount N of correctly identified training images, and get the image recognition rate by computing correctly identified training images and total training images.

5. Simulation Experiments

In order to test and improve the effectiveness of algorithm in this paper in face image recognition, images in Yale B face database are used for simulation experiments. The simulation environment is: software is Core dual-core i32.0 GHz, memory is 4GDDR3, software is MABLAB7.0 with Windows XP operation system. There are altogether 5760 face images in Yale B, including 9 expressions of 10 people, and each expression has 64 images in different lighting conditions. Because in this paper, only the influence of lighting changes to recognition is discussed, so images of each subset in one expression and of the same people are chosen for the experiment. Take two people for instance, take one image from 5 subsets respectively, and original lighting changes are as shown in Figure 2.

Figure 2. Images of Original Lighting Changes

5.1 Contrast of Processed Image Effects

Effects of processed images are as shown in Figure 3. It can be seen from Figure 3 that although the overall face images affected by lights can be enhanced by traditional BP algorithm, the processing of local details of face images is not ideal. Improved BP algorithm can not only effectively enhance the dark area of face images affected by lights, and highlight details originally hidden in the dark, but also maintain bright regions in the images, and the effects of image light pretreatment is significantly better than that of BP algorithm.

(a)Face Images Processed by BP Algorithm

(a) Face Images Processed by Improved BP Algorithm

Figure 3. Effects of Face Images Processed by Different Algorithms

5.2 Comparison of Objective Quality Evaluation Criteria

In order to illustrate the problem more definitely, objective quality evaluation standard is used to validate the effectiveness of the algorithm and entropy, average brightness and contrast are adopted as the evaluation indexes. Figure 4-6 shows the contrasting results of information entropy, brightness and contrast of testing samples with the amount ranging from 0 to 100.

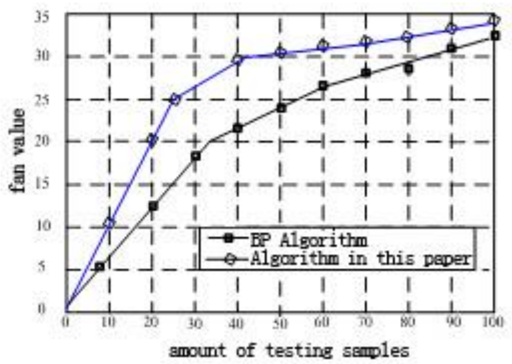

Figure 4. Comparison of Image Information Entropy of Different Algorithms

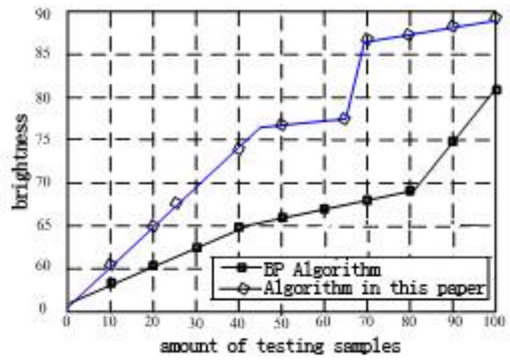

Figure 5. Comparison of Image Brightness of Different Algorithms

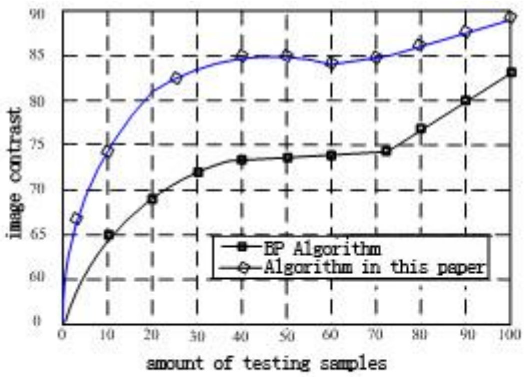

Figure 6. Comparison of Image Contrast of Different Algorithms

It can be known from Figure 4-6 that among the three image quality evaluation indexes, the results of improved BP algorithm are superior to contrast algorithm. It can make effective pretreatment to face image lighting and solve the difficult problem of face recognition well to some extent, thus greatly improving the quality of images in the face region.

6. Conclusion

In this paper, Gabor algorithm is mainly used to extract data of major features of images in face database, BP parameters are determined by extracted image data, and BP neural network is improved for recognition by improved weight learning method. Simulation experiment shows that algorithm in this paper can effectively improve face recognition rate with better convergence speed and higher recognition rate.

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