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Face Recognition based on Improved Robust Sparse Coding Algorithm

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Abstract

In order to improve the performance of face recognition, a novel face recognition method based on improved robust sparse coding algorithm (MRCS-ELM) to solve the defecting of traditional sparse coding algorithm. Firstly, the face images are collected and pretreated, and then the robust sparse coding algorithm is used to encode the face features, and the robust sparse coding algorithm is modified, finally, the features are input to extreme learning machine to established the face classifier and the simulation experiment is used to testing performance by using AR face data. The results show that the proposed model has improved the recognition rate and reduces the computational complexity greatly compared with other models, and it has strong robustness to face recognition.

Keywords: *face recognition; sparse representation; extreme learning machine; features extraction*

1. Introduction

As a major means of identification, face recognition broad application prospects in public security, digital authentication, video monitoring and other fields, and after decades of development, the research of face recognition has made a lot of achievements [1]. However, there are still many problems to be solved with face recognition technology, e.g. recognition of occluded face images [2].

Because the recognition of occluded face has more practical value, scholars both at home and from abroad have conducted a lot of research on it in the past twenty years, and have put forward some robust face recognition models. Feature extraction is very critical for face recognition, and its integrity has an important influence on the subsequent recognition [3]. Local binary pattern method is proposed in Literature [4] and negative impact of environmental factors are eliminated through introducing variables; Gabor filter is proposed in Literature [5] to extract human faces' local characteristics. Although it is not sensitive to environmental changes, it has improved the accuracy and robustness of face recognition; the face recognition method based on hyper-graph Laplace characteristics of face is proposed in Literature [6] and it can extract face features better and obtain relatively ideal facial recognition results. However, feature dimensions of these face recognition methods are quite large, affecting the efficiency of face recognition and it is easy to cause "dimension disaster". Therefore, some scholars adopt the method to reduce dimension by extracting some features, e.g. principal component analysis, liner discriminant analysis, etc [7, 8]. These methods can effectively remove duplications and useless features, but can also remove some effective characteristics with relatively poor interpretability at the same time.

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Therefore, John Wright has proposed the Sparse Representation based Classification (SRC), in which we can get good recognition accuracy at the occluded part of face by sparse coding human face. On the basis of SCR, Yang has proposed the Robust Sparse Coding (RSC) algorithm, in which models are established by seeking the estimation of maximum likelihood of sparse coding problems so as to further increase the accuracy of face recognition [10]. However, in the actual application process of face recognition, L1 norm sparse constraint is used in SRC, resulting high computational complexity of face recognition, and thus affecting the real-time of face recognition. Face recognition is not only related to face features, but also with human face classifiers, which is built based on neural network and supporting vector machine [11, 12]. However, they all have their own limitations, e.g. slow training speed of neural network, which is easy to fall into local optimum. SVM has difficulties in solving problems and the large-scale training samples are hard to implement, influencing the performance of face recognition. Extreme Learning Machine (ELM) is a training method of feed-forward neural network, which sets the preliminary weights of feed-forward neural network at random and completed the network training by working out the minimum square solutions to the output weights. It has overcome the deficiency of neural network and supporting vector machine, so it can be used to build establish face recognition classifier [13].

In order to improve the performance of face recognition, a face recognition model to improve the robust sparse coding (MRCS-ELM) is proposed aiming at the deficiency of robust sparse coding (RSC). First, work out the maximum likelihood of the sparse coding problems by using the robust sparse codes, and then solve the MRSC model by using the iterative weighted cooperative representation algorithm. Finally, establish classification model of face images by extreme learning machine and conduct simulation experiments in the AR face database. The results have shown that, compared with other face recognition models, MRCS-ELM has improved the accuracy of recognition and reduced the computational complexity in the process of face recognition.

2. MRCS-ELM Face Recognition Model

2.1 Process of Face Recognition

The process of MRCS-ELM face recognition method is shown in Figure 1. First, collect face images and make pre-treatment. And then extract effective face features by MRCS and eliminate useless face features. Finally, establish face multiple classifier by adopting ELM, and classify the recognized faces and put out the results.

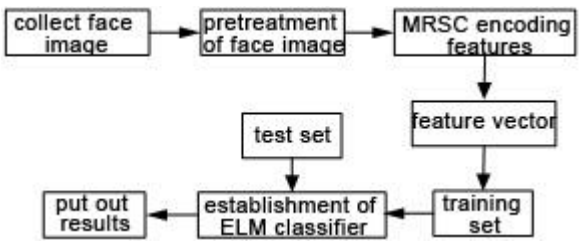

Figure 1. Workflow of Face Recognition Method

2.2 Pre-treatment of Face Image

The process of acquiring faces is affected by many factors. Therefore, it must be pretreated. Gabor filter is not sensitive to environmental changes, so first use the Gabor filter to make pre-treatment of face images to eliminate the noises. The Gabor filter with direction μ and measure v is

$$\Psi_{u,v}(z)=\frac{\left\|k_{u,v}\right\|^2}{\delta^2}e^{(-\left\|k_{u,v}\right\|^2\left\|z\right\|^2/2\delta^2)}[e^{ik_{u,v}z}-e^{-\delta^2/2}] \tag{1}$$

Among them, $z=(x,y)$ is the pixel coordinates; $k_{\max}$ is the maximum frequency; σ determines the filter bandwidth; "＊" represents convolution operation.
The small filter coefficient is:

$$\chi=(\boldsymbol{a}_{0,0}^{(\rho)^T}\boldsymbol{a}_{0,1}^{(\rho)^T},\cdots\boldsymbol{a}_{0,7}^{(\rho)^T};\boldsymbol{a}_{1,0}^{(\rho)^T}\cdots\boldsymbol{a}_{4,7}^{(\rho)^T}) \tag{2}$$

2.3 Sparse Representation Based Face Recognition

Robust sparse coding method (RSC) is s representative robust face recognition method. Assume the encoding residual meets random distribution, so estimate the sparse coefficient by maximum likelihood function, and then RSC mode is:

$$\begin{aligned}&\min_{\alpha}\sum_{i=1}^{n}\rho_\theta(y_i-r_i\alpha)\\&s.t.\\&\left\|\alpha\right\|_1\le\sigma\end{aligned} \tag{3}$$

In the formula, $\rho_\theta=-\ln f_\theta(e_i)$ is the target function, θ is the function describing the distribution, r_i constitutes a dictionary, $f_\theta(e_i)$ is the symmetric probability density function, e_i is the i element of coding residual.

Set the $F_\theta(e)=\sum_{i=1}^{n}\rho_\theta(e_i)$, and expand it with the 1st order formula Taylor at the neighborhood e_0:

$$\tilde{F}_\theta(e)=F_\theta(e_0)+(e-e_0)^T F_\theta^{'}(e_0)+R_1(e) \tag{4}$$

In the formula, $R_1(e)$ is the high order residual item, $F_\theta^{'}(e_0)$ is the derivative of $F_\theta(e)$.

$F_\theta(e)$ gets the minimum value at $e=0$, set $F_\theta^{'}(0)=0$, then the diagonal matrix elements $W_{i,j}$:

$$W_{i,i}=w_\theta(e_{0,i})=\rho_\theta^{'}(e_{0,i})/e_{0,i} \tag{5}$$

Because $\tilde{F}_\theta(e)$ can be wrote as the 2 norm form, then formula （3）can be changed to:

$$\begin{aligned}&\alpha^*=\min_{\alpha}\left\|W^{1/2}(y-D\alpha)\right\|_2^2\\&s.t.\\&\left\|\alpha\right\|_1\le\sigma\end{aligned} \tag{6}$$

Find the optimal solution α^* by transforming (6) into an iterative weighted sparse coding problem, $W_{i,i}$ is assigned to each pixel of the test image y, then $W_{i,i}$ has new meaning, that is, weight factor[14].

The operation of RSC is an iterative process, and each iterative process is a $l1$ minimum convex optimization problem. In the iterative process, when the difference

between two adjacent weight values is very small, convergence has been achieved. But when the condition is as the following formula, the iteration is stopped:

$$\left\|W^{(t)}-W^{(t-1)}\right\|_2 / \left\|W^{(t-1)}\right\|_2 < \gamma \tag{7}$$

In the process of solving the RSC model by using iterative sparse coding algorithm, the number of iterations is very large though. Besides, we need to work out the solutions to formula (7) during the process of iteration, and it has increased the computational complexity. In order to reduce the computational complexity and improve the efficiency of face recognition, an algorithm based on improving robust sparse coding (MRCS) is proposed. In order to use the training sample set D to represent the test sample y collaboratively, the minimum square method is used, that is:

$$\hat{\alpha} = \arg\min_{\alpha}\left(\left\|y-D\alpha\right\|_2^2 + \lambda\left\|\alpha\right\|_2^2\right) \tag{8}$$

In the formula, λ is the regularization parameter.

Solution to formula (7) can be derived, that is:

$$\hat{\alpha} = \left(D^T D + \lambda \cdot I\right)^{-1} D^T y \tag{9}$$

For the test sample y, get its coding vector $\hat{\alpha}$ by projection, that is:

$$\hat{\alpha} = \arg\min_{\alpha}\left(\left\|W^{1/2}\left(y-D\alpha\right)\right\|_2^2 + \lambda\left\|\alpha\right\|_2^2\right) \tag{10}$$

When W is given, we can get solution to formula (8), that is:

$$\hat{\alpha} = \left(D^T W D + \lambda \cdot I\right)^{-1} D^T W y \tag{11}$$

2.4 ELM Classification Algorithm

Assume there are N training sample sets (x_i, t_i), in which $x_i = [x_{i1}, x_{i2}, \cdots x_{in}]^T \in R^n$, $t_i = [t_{i1}, t_{i2}, \cdots t_{im}]^T \in R^m$, the activation function of ELM network is $g(x)$, the hidden layer node number is L, the training process of ELM algorithm is:

(1) The connection weights and bias of network is given at random:

$$(a_{i,..} b_i), i = 1,2,\cdots,L \tag{12}$$

(2) The activation function of hidden layer is g(x), the output of feed-neural network can be expressed as:

$$f_L(x) = \sum_{i=1}^{L} \beta_i G(a_i \cdot x_i + b_i)$$

$$x \in R^n, a_i \in R^n, \beta_i \in R^m \tag{13}$$

The above formula can be shortened as:

$$H\beta = Y \tag{14}$$

Herein, the output matrix H of network hidden layer can be expressed as:

$$H = \begin{bmatrix} G(a_1 \cdot x_1 + b_1) & \cdots & G(a_L \cdot x_1 + b_L) \\ \cdots & \cdots & \cdots \\ G(a_1 \cdot x_N + b_1) & \cdots & G(a_L \cdot x_N + b_L) \end{bmatrix}_{N \times L} \quad \beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L \times m} \quad Y = \begin{bmatrix} y_1^T \\ \vdots \\ y_N^T \end{bmatrix}_{N \times m}$$

(3) The output weight matrix can be obtained by the following formula:

$$\tilde{\beta} = H^{+}Y \tag{15}$$

In the formula, represents the Moore-penrose generalize inverse of hidden layer's output matrix.

3. Simulation Experiments

In order to test the effectiveness of the MRCS-ELM model, VC++ is adopted to achieve simulation experiments on the platform of P4 4 cores 2.8GHz CPU，4GB RAM，Windows XP, and select AR face database as the simulation object [16]. And select RSC-Elm, MRSC and support vector machine (SVM) to make comparative experiments of face recognition model (MRSC-SVM), MRSC and face recognition model of neural network under the same conditions to test the superiority of MRCS-ELM.

The AR face database includes 2599 images of 100 people with 26 of each people and 50 men and 50 women. Normalize the image as 42×30, select images with expressions in subset 1 and 2 as the training set, and establish classifier model of face images. Then take the images of faces with dark glasses and scarf as the test set to test the effectiveness of the test models. Some training and test images of the face database are shown in Figure 2.

(a) Some Training Images

(b) Some Test Images

Figure 2. A Small Portion of Test Samples in AR Face Database

The comparison of recognition accuracy and average operation time of different models in the AR face database are shown in Figure 3 and Figure 4 respectively, in which the average operation time refers to the average operation time of each test image.

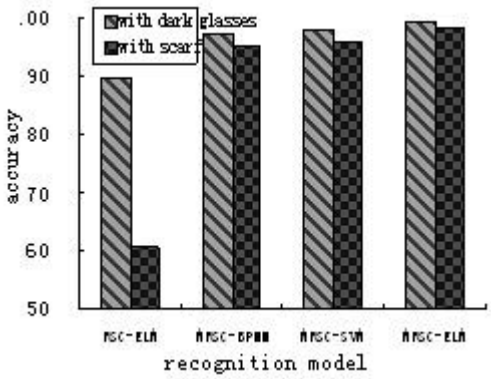

Figure 3. Comparison of Different Models' Recognition Accuracy

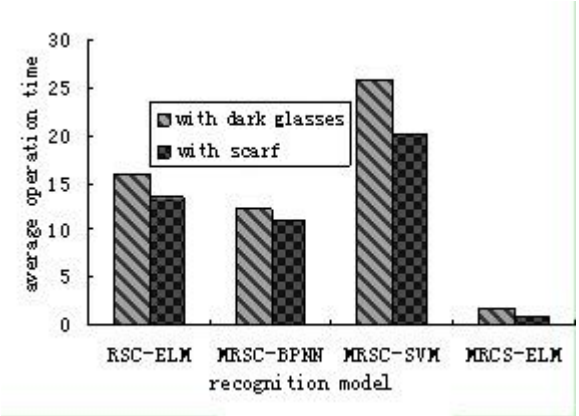

Figure 4. Comparison of Different Models' Recognition Speed

Through comparison of the identification results of each face model in Figure 3 and Figure 4, we can get the following conclusions:

(1) Compared with the RSC-ELM model, MSRC-ELM has greatly improved the accuracy of faces with dark glasses and scarf. Meanwhile, it has accelerated the operation speed of face recognition models, and the recognition accuracy of faces with dark glasses has improved by 9.42% while that of faces with scarf has improved by 37.45%. The comparison results have shown that RSC algorithm is improved to select better characteristics of face recognition and eliminate the useless face features in this paper. Meanwhile, it has reduced the computational complexity of classifiers and improved the accuracy of face recognition, so it is able to meet the application requirements of high recognition accuracy and efficiency with more practical application values.

(2) Compared with MRSC-SVM and MSRC-BPNN, the performance of MSRC-ELM to recognize faces with dar glasses and scarf have improved to varying degrees. This indicates that the selection classifiere have great impacts on the results of face recognition, besides, ELM has overcome the defficiencies like long training time as well as low efficiency of neural network fitting, dimension disaster and supporting vector machines, and estavlished face classifier with better performance. So it has some certain advantages.

4. Conclusion

In order to improve the performance of face recognition, a face recognition model to improve robust sparse coding algorithm is proposed. First, make pre-treatment to the collected face images to eliminate the negative effects of environment on the image quality preliminarily. Then extract and select features of face images by improving robust sparse coding algorithm. And finally, learn the featured vectors by adopting extreme learning, and set face classifier. Make simulation experiments at the AR and Yale B face database, and the results have shown that MRCS-ELM has improved the identification accuracy of faces and gets relatively ideal face recognition results. Besides, it has accelerated the speed, so it is an effective face recognition model.

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