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The Design of Face Recognition System based on MATLAB

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***Abstract*—This design is based on MATLAB, through PCA image drop-down technology to reduce the image in the face library to low-dimensional, and then through the MATLAB installation LIBSVM Toolbox, that is, through the SVM support vector machine classifier way to classify the picture data, in order to achieve face recognition.**

Keywords—face recognition;image processing; dimension reduction

I. INTRODUCTION

The research on face recognition technology has been started very early, and the year that is more important for the nationwide research on face recognition technology is the Olympic Games held in China in 2008, because face recognition technology is in the security work of the Olympic Games. It has played a key role and has attracted widespread attention in the face recognition industry. The face recognition system at the Beijing Olympics was independently developed by the Institute of Automation of the Chinese Academy of Sciences. It has enabled China's face recognition technology to develop very well and has allowed China to lead the international community in this technology field.

The earliest application of face recognition technology is the public security department's archival work on the photos of criminals, and at the same time used to detect the auxiliary effects of the case, and with the continuous advancement and development of technology, the function of the face recognition system is more and more perfect. . In today's society, both government departments, state units, and business firms in all walks of life have applied face recognition technology. The main applications of this technology include: information security, access control, video surveillance, identity authentication, and case detection.

Compared with other biometrics, face recognition technology can not be easily copied, unique, reliable and stable features, so it has better security effects for identity recognition. Therefore, face recognition technology has been increasingly recognized by the society, and face recognition technology has therefore been applied to many industries in the society. The research on face recognition technology can help to study the theoretical basis and the integration of knowledge research and development in related fields, and it is also conducive to the development of innovative projects. In short, the development of society is inseparable from innovation. In the case of face recognition technology, the development can lead a country to continuous innovation, bringing new vitality and motivation to the society, bringing convenience to people's lives [1].

II. DIMENSIONALITY REDUCTION

When the image is recognized, the matrix is usually used to represent the image of the face. However, the recognition system is very slow in recognizing the high-dimensional image data, which is easy to cause the system to collapse, and is not conducive to the real-time recognition system. Realization, so to solve this problem, we need to use dimensionality reduction technology to transform data from high-dimensional image space to low-dimensional feature space, and at this time, most of the original image data can be retained. In 1991, Turk proposed the famous Eigen face method, which applied principal component analysis (PCA) to face recognition technology. The face recognition method was carried out by extracting the main components of the face image. The PCA algorithm has a high recognition speed and a correct rate of recognition, and is also robust to changes in expression and slight tilt [2] [3].

Regarding the principle of the PCA algorithm, we must first know the mathematical formula of the covariance matrix in these higher mathematics, the mean of the sample: $\bar{X} = \frac{\sum_{i=1}^{n} X_i}{n}$, the standard deviation formula of the sample: $s = \sqrt{\frac{\sum_{i=1}^{n}(X_i - \bar{X})^2}{n-1}}$, the formula of the variance of the sample: $s^2 = \frac{\sum_{i=1}^{n}(X_i - \bar{X})^2}{n-1}$, the standard deviation and the variance are generally used to describe the one-dimensional Data, but in most cases is the data set of multidimensional data, then the covariance is used to measure the statistics of the relationship between two random variables, as defined below:

$$\mathrm{Cov}(X, Y) = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{(n-1)}$$

Covariance is used to deal with two-dimensional problems, and multiple covariance matrices can deal with multi-dimensional problems, so we need to use matrix to organize these multi-dimensional data. Covariance matrix is defined as: $C_{n\times n} = (c_{i,j}, c_{i,j} = cov\left(Dim_i, Dim_j\right))$, Covariance matrix is a symmetric matrix and the diagonal is the variance in each dimension. The covariance matrix is to calculate the covariance between different dimensions. The sample matrix can be centered first, that is, the mean of the dimension is subtracted from each dimension, and then the transposed is directly multiplied by the newly obtained sample matrix, and finally divided by (N-1). It is very important to calculate the eigenvalue and eigenvector of the covariance matrix after calculating the mean value. Because the covariance matrix is a square matrix of N*N, the dimension N should be equal to the original image matrix(200*10304) dimension. . Then the feature vector is unitized, because the feature vector of the unit painting is the basis of the low-dimensional space, and it is necessary to satisfy the two conditions of orthogonalization unitization. Finally, the eigenvector of the unit orthogonalization is multiplied by the centralized sample matrix. It is possible to obtain the coordinate representation of the image data in a low-dimensional space, that is, the basis for an image discrimination.

In the PCA image dimensionality reduction, the image is reduced to 20 dimensions, so the base of the low-dimensional is the 20 feature faces, and all other dimensionally reduced faces can be linearized by the feature face.

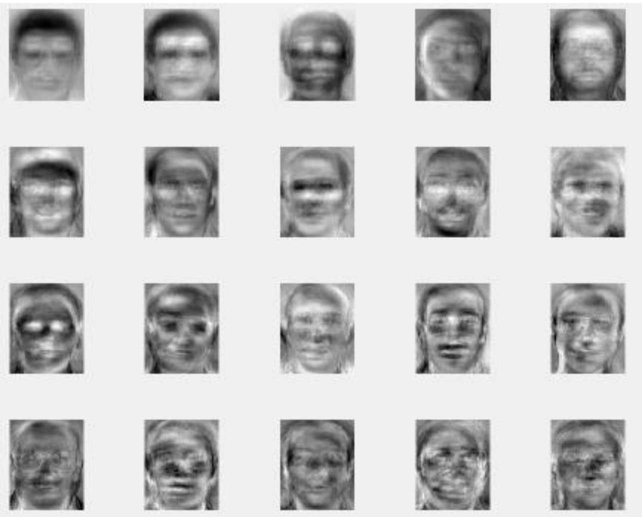

Fig. 1. Eigen Face

III. FACE RECOGNITION

In the face recognition program, SVM is used to train the training set to get the established model, and then find a sample to identify. When training the sample, there are two important functions in the libsvm toolbox: svmtrain function. And the svmpredict function, expressed in MATLAB:

[select_predict_label,accuracy,decision_values]=svmpredict(select_person_num,select_matrix,model), where select_predict_label represents the label of the training set, and select_matrix represents the attribute matrix of the training set, where the kernel The linear kernel function chosen by the function.

Given input data and learning objectives $\mathrm{X} = \{X_1, \ldots X_N\}, \mathrm{y} = \{y_1, \ldots y_N\}$, Hard-boundary SVM is an algorithm for solving the maximum-margin hyperplane in a linearly separable problem. The constraint is that the distance from the sample point to the decision boundary is greater than or equal to 1. The hard boundary SVM can be transformed into an equivalent quadratic convex optimization problem.

$$\max_{w,b} \frac{2}{\|w\|} \quad \Leftrightarrow \quad \min_{w,b} \frac{1}{2}\|w\|^2$$

$$s.t.\ y_i(w^T X_i + b) \geq 1 \quad s.t. y_i(w^T X_i + b) \geq 1$$

The decision boundary obtained by the above formula can classify any sample：$\mathrm{sign}[y_i(w^Y X_i + b)]$.It is noted that although the hyperplane normal vector is the only optimization target, the interception of the learning data and the hyperplane affects the optimization problem through the constraint conditions. The hard margin SVM is the soft margin SVM when the regularization coefficient is 0. For the dual problem and solution, see the soft margin SVM, which is not listed here.

The use of hard-spacing SVM in linear inseparable problems will produce classification errors, so a loss function can be introduced to maximize the margins to construct a new optimization problem. The SVM uses the hinge loss function, which follows the optimization problem of the hard-boundary SVM. The optimization problem of the soft-margin SVM is as follows:

$$\min_{w,b} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N} L_i\,, L_i = \max[0, 1 - y_i(w^T X_i + b)]$$

$$\mathrm{s.t.} \quad y_i(w^T X_i + b) \geq 1 - L_i, \quad L_i \geq 0$$

The above equation shows that the soft margin SVM is an L2 regularization classifier, which represents the hinge loss function. Using slack variables: After processing the segmentation value of the hinge loss function, the above equation can be transformed into:

$$\min_{w,b} \frac{1}{2}\|w\|^2 + c\sum_{i=1}^{N} \xi_i$$

$$\mathrm{s.t.} \ \ y_i(w^T X_i + b) \geq 1 - \xi_i, \ \ \xi_i \geq 0$$

The optimization problem of defining soft margin SVM is the primal problem. Lagrange multiplier）：$\alpha = \{\alpha_1, \ldots \alpha_N\}, \mu = \{\mu_1, \ldots \mu_N\}$ Lagrange multiplier can be used to obtain its Lagrangian function.

$$\mathcal{L}(\mathrm{w},\mathrm{b},\xi,\alpha,\mu)=\frac{1}{2}\|w\|^2+c\sum_{i=1}^{N}\xi_i+\sum_{i=1}^{N}\alpha_i[1-\xi_i-\ y_i(w^TX_i+b)]-\sum_{i=1}^{N}\mu_i\xi_i$$

Let the Lagrangian function have a partial derivative of 0 for the optimization target, and get a series of expressions containing Lagrangian multipliers.

$$\frac{\partial\mathcal{L}}{\partial w}=0\ \Rightarrow w=\sum_{i=1}^{N}\alpha_i y_i X_i\ ,$$

$$\frac{\partial\mathcal{L}}{\partial b}=0\ \Rightarrow \sum_{i=1}^{N}\alpha_i y_i=0,$$

$$\frac{\partial\mathcal{L}}{\partial\xi}=0\ \Rightarrow\ C=\alpha_i+\mu_i$$

Bring it into the Lagrangian function to get the dual problem of the original problem

$$\max_{\alpha}\sum_{i=1}^{N}\alpha_i-\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}[\alpha_i y_i(X_i)^T(X_j)y_j\alpha_j]$$

$$\mathrm{s.t.}\quad \textstyle\sum_{i=1}^{N}\alpha_i y_i=0,\ \ 0\le\alpha_i\le C$$

The constraint of the dual problem contains unequal relations, so its local optimal condition is that the Lagrangian multiplier satisfies the Karush-Kuhn-Tucker condition (KKT).

$$\begin{cases}\alpha_i\ge 0\ ,\mu_i\ge 0\\ \xi_i\ge 0,\mu_i\ \xi_i=0\\ y_i(w^TX_i+b)-1+L_i\ge 0\\ \alpha_i[\ y_i(w^TX_i+b)-1+L_i]=0\end{cases}$$

Regarding the face recognition part, when the program runs, an input box will pop up, allowing the user to select the picture to be recognized. When Accuracy=100% indicates that the recognition is correct, if Accuracy=0% indicates recognition error.

Fig. 2. *Recognition Result*

IV. CONCLUSION

The system can realize the compression processing of the image data, extract the relevant features of the face to obtain the feature face, and then use the feature face as the basis of the face recognition. The processed image is a face in the ORL face database, and the face in the face database is labeled in the program, and the result of the program running is to prompt the user to input the number and face number of the first person to be identified, thereby get the original image and the matching image. Sometimes there is a case of matching errors. The correct recognition rate of the selected algorithm PCA is that there is an extreme point problem. As the dimension of the fusion feature space increases, the correct recognition rate will gradually increase and eventually stabilize. Secondly, the PCA algorithm can only recognize grayscale images, so it is relatively sensitive to lighting conditions.

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