Research on Library Face Book Return Model based on Hybrid PCA and Kernel Function

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***Abstract*—With the improvement in the quality of university education in China, the behavior of college students and school teachers to borrow and return books in the library is becoming more and more frequent. In peak periods of returning books, managers cannot even assist in returning books in time. Therefore, this research uses kernel function, multi-dimensional principal component analysis method, and multi-dimensional linear discriminant analysis method to construct a new face recognition algorithm for the automatic return of books in the university library. The test results show that the XT_2D_PL algorithm designed in this study has a face recognition rate of 96.8%. When the number of face samples of each type in the test sample set is 11, and when the number of feature dimensions is 14, the recognition rate of 96.3% reaches the highest level. However, if the sample to be processed is 500 pictures, the calculation speed is 1.072ms/per photo, higher than most comparison algorithms. The proposed face recognition algorithm has high recognition accuracy on the library face data; the calculation speed meets the needs of practical applications, and has certain practical promotion potential.**

Keywords—Kernel function; multidimensional principal component analysis; face recognition; intelligent book return

I. Introduction

The traditional way of returning books in university libraries is that the returner puts his valid borrowing certificate in the designated sensing area to identify his identity, returns the book, and takes it away [1-2]. The whole process of returning books in the library is cumbersome, and book returners often forget to carry valid borrowing certificates, which lead to the failure of book return and wastes the time and energy of book returners [3]. Therefore, some university administrators and technical experts propose applying advanced face recognition technology to the library return process and building a university library intelligent return model, so that book returners do not need to carry additional documents and only use their social biometric information and the book return process can be completed [4]. However, the recognition accuracy of algorithms used in the same type of products in the current market still needs to be improved. Directly using the face recognition algorithms of these products to build an intelligent book return system may lead to face-matching errors, face recognition failures, and other problems. This is also the main gap between previous research results and market applications. Therefore, it is necessary to design an algorithm with higher facial recognition accuracy for the intelligent face book return model of college students in order to solve such problems. Therefore, it is necessary to design an algorithm with higher recognition accuracy for the intelligent face book return model of college students. This research attempts to use multidimensional principal component analysis and multidimensional linear discriminant analysis to reduce the dimension of face data, reduce the redundant information in the image, highlight the key image features, and combine the kernel function to map the reduced data to the high-dimensional feature space, stoned a more suitable classification and recognition space, which is also the innovation of this research. The significance of this study is to improve the efficiency of library borrowing and returning books, reduce the losses caused by work errors of library management personnel, and provide useful references for improving the borrowing experience of borrowing personnel. The significance of this study is to improve the efficiency of library borrowing and returning books, reduce the losses caused by work errors of library management personnel, and provide useful references for improving the borrowing experience of borrowing personnel. The content of this article can be divided into four major sections. The second section is used to elaborate and compare relevant research at home and abroad, and to introduce the purpose of conducting this research. The third module is to design an improved model for face recognition. The main content of the fourth module is to design and carry out experiments to verify the performance of the designed library face recognition model. The main content of the fifth module is to summarize the experimental results of this study and point out the direction for future research.

II. Related Works

To apply face recognition technology to more real-life scenarios and improve identification quality, scientists and scholars have carried out a lot of related research. Timur I et al. found that hierarchical temporal memory, a new type of machine learning algorithm, performed better in some supervised learning tasks, so they proposed a hierarchical temporal memory algorithm with a learning mechanism. The important features of all images create templates, thereby greatly reducing the computer memory requirements of the algorithm and increasing the calculation speed of the algorithm. The face recognition results show that the recognition accuracy of this algorithm is significantly improved compared with the unimproved hierarchical time memory algorithm when recognizing a large amount of face data [5]. Scholar Clwa found that the face recognition algorithm can be applied to the recognition of other primates such as chimpanzees, but it cannot be applied to the recognition of rhesus monkeys, but rhesus monkeys are widely used in biomedical research and can be effectively recognized; conducive to the development of auxiliary medical research.

Therefore, researchers combine the face recognition method with face detection technology to design a new rhesus monkey face recognition algorithm. The test results show that the method has high classification accuracy [6]. Hansen et al. used the common VGG model in face recognition, the Fisherfaces algorithm, and their algorithm to recognize the face of artificially raised pigs, and found that the algorithm they designed had the highest recognition accuracy on 1553 pig face pictures [7]. Lu et al. found that the resolution of face images captured by surveillance cameras is low, which will adversely affect the performance of gallery image matching. Therefore, they proposed an improved ResNet algorithm incorporating the idea of deep coupling, using a variety of face recognition algorithms in training. The commonly used data sets are tested, and the results show that the proposed algorithm has better consistency and judgment accuracy compared with the existing algorithms [8]. Bours et al. found that autism spectrum disorder is related to the difficulty of emotional recognition of patients through face recognition technology [9]. Ahmed et al. used the Gabor wavelet transform to construct a face recognition algorithm for recognizing symmetrical face images. The test results show that the recognition accuracy of the algorithm on various face recognition task datasets is higher than that of common neural network algorithm [10]. Wu found that the recognition accuracy of many face recognition systems declined during the COVID-19 epidemic. This is because many face recognition systems were trained based on face image data with no or little occlusion. The face image recognition ability is poor. Therefore, in this study, to improve the recognition accuracy of large-area-covered face images, a face recognition algorithm integrated with the attention mechanism was designed. The test results show that the algorithm has significantly higher recognition accuracy on face image data with large area coverage than the traditional face recognition algorithm [11]. Martins et al. studied the recognition performance of the parallax energy model in an expression-invariant facial recognition system and found that the model significantly improved the measurement performance compared with the accurate laser ranging map calculation results [12]. Jain et al. found that deep neural networks outperformed traditional machine learning algorithms in processing face image recognition tasks containing facial expressions, so they proposed a hybrid convolutional recurrent neural network algorithm, which consists of convolutional layers and recursive neural networks; neural network composition. The test results show that, compared with the existing algorithms with better processing performance for face recognition tasks with expressions, the algorithm can obtain higher recognition accuracy and the calculation speed can also meet most application scenarios [13].

In summary, the current artificial intelligence experts have carried out a lot of research to improve the accuracy and speed of face recognition in different application scenarios, and have proposed some algorithms or improvement ideas that can practically solve the problem. However, due to the characteristics of face images that need to be processed in the university library's face return book model, there are fewer expressions, more environmentally redundant information, and higher image similarity, so the previous research results cannot be directly used. Therefore, this research attempts to design a targeted face recognition algorithm according to the data characteristics in the library face book return scene.

III. Building a Library Face Book Return Model Combining Kernel Function, PCA and LDA

A. Design of Bidirectional Linear Feature Extraction Algorithm based on 2D PCA and 2D LDA

In the face recognition problem, due to the high feature dimension in the face image data, appropriate dimensionality reduction processing will help to improve the face recognition effect [14-15]. Principal Component Analysis (PCA) is an effective and commonly used linear data dimensionality reduction algorithm, and its dimensionality reduction principle is shown in Fig. 1.

As shown in Fig. 1, this method treats the face image as a high-dimensional vector and maps the data to a lower-dimensional feature subspace according to the criterion of maximizing the variance of the principal component data after dimension reduction [16]. The Linear Discriminant Analysis (LDA) method is a classic pattern recognition method. Due to its extremely low computational complexity and simple computational logic, it can also be used to process face data [17]. The calculation principle of the LDA method is shown in Fig. 2.

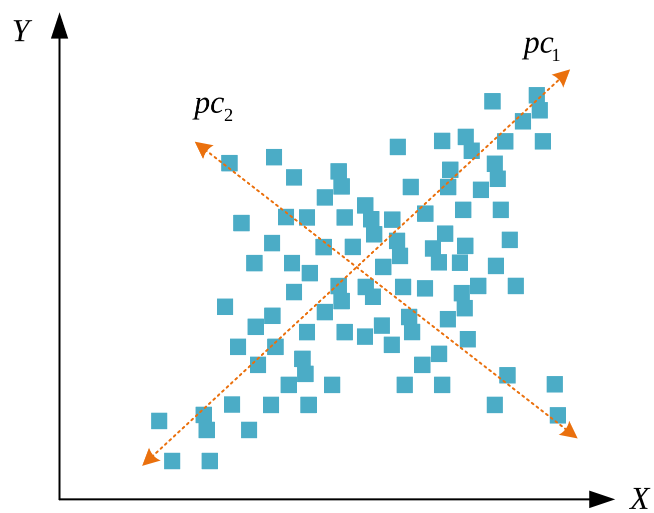
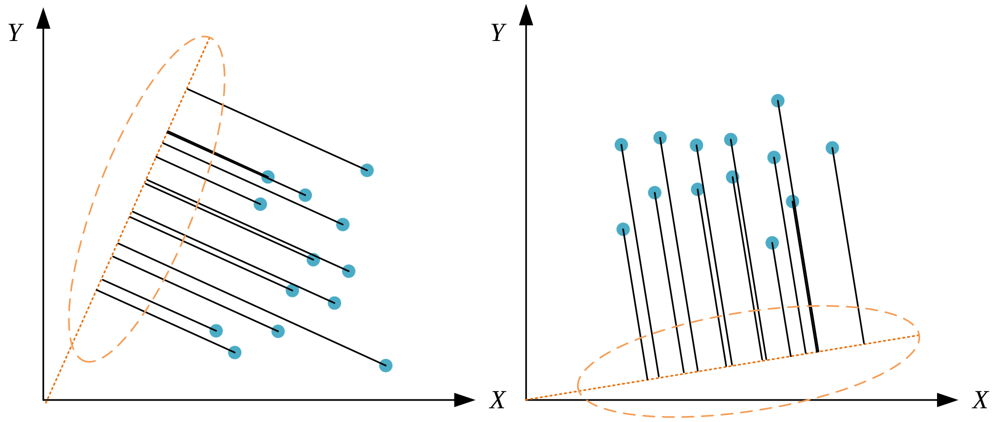


Fig. 1. Schematic diagram of PCA algorithm dimensionality reduction.



(a) (b)

Fig. 2. Calculation schematic diagram of the LDA method.

To be processed to an optimal classification direction in a way that makes the heterogeneous samples mapped in a certain direction has the largest distance in space or the most dispersed distribution, to achieve data classification. However, PCA has the disadvantage of not using the original sample type, and LDA also has limitations when dealing with small samples [18-19]. Therefore, to improve the processing speed and processing accuracy of face data, and consider the multi-directional correlation of data, a bidirectional linear feature extraction algorithm based on two-dimensional PCA and two-dimensional LDA (hereinafter referred to as T_2D_PL algorithm) is proposed. In the T_2D_PL algorithm, the rows in the horizontal direction and the columns in the vertical direction are processed at the same time to obtain the optimal projection axis [20]. When the algorithm is applied to face image dimensionality reduction, it is equivalent to projecting the face image to the column direction, that is, two-dimensional LDA and row direction, that is, the optimal projection of 2DPCA, and according to the feature matrix variance maximization and Fisher criterion The optimization is carried out in a maximizing way so that the number of output feature vectors is greatly reduced, and the data dimensionality reduction is completed. In the T_2D_PL algorithm, if the original image is A_i, and the average image is μ, then the two can be expressed by formula (1).

$$\begin{cases} A_i = \left[(a_i^{(1)})^T, (a_i^{(2)})^T, \ldots, (a_i^{(m)})^T \right]^T \\ \mu = \left[(v^{(1)})^T, (v^{(2)})^T, \ldots, (v^{(m)})^T \right]^T \end{cases} \tag{1}$$

Among them $a_i^{(j)}$, $v^{(j)}$ represent the row vector of the i th sample A_i and μ the th row respectively j, then the covariance matrix G can be expressed by formula (2).

$$G = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{M} \left(a_i^{(j)} - v^{(j)} \right)^T \left(a_i^{(j)} - v^{(j)} \right) \tag{2}$$

Where N and M represent the total number of samples and the row vector size of the average image, respectively. It can be seen from Eq. (2) that the operation object of the image covariance matrix is the row vector of the matrix. G After the eigenvalues are decomposed, the former d eigenvectors are formed into a projected multidimensional vector space X_{opt}. In the column direction, the algorithm uses the two-dimensional LDA method to find the best projection vector Z to maximize the Fisher function, as shown in Eq. (3).

$$J(\tau) = \frac{Z^T S_{FB} Z}{Z^T S_{FW} Z} \tag{3}$$

In formula (3), S_{FB} and, S_{FW} represent the inter-class scatter matrix and the intra-class scatter matrix, respectively, which are represented by formulas (4) and (5), respectively.

$$S_{FB} = N^{-1} \sum_{i=1}^{C} N_i \left(\bar{A}_i - \bar{A} \right) \left(\bar{A}_i - \bar{A} \right)^T \tag{4}$$

Eq. (4) $\bar{A}_i$ represents the mean of the i th image sample, which is the mean $\bar{A}$ of the total samples of all images.

$$S_{FW} = N^{-1} \sum_{i=1}^{C} \sum_{j \in C_i} \left(A_j - \bar{A}_i \right) \left(A_j - \bar{A}_i \right)^T \tag{5}$$

Obtaining S_{FB} and S_{FW} calculating, $S_{FW}^{-1} S_{FB}$ the optimal projection matrix can be obtained, which consists of the previous d largest eigenvalue of the calculation result. To sum up, the calculation flow of the T_2D_PL algorithm can be shown in Fig. 3.

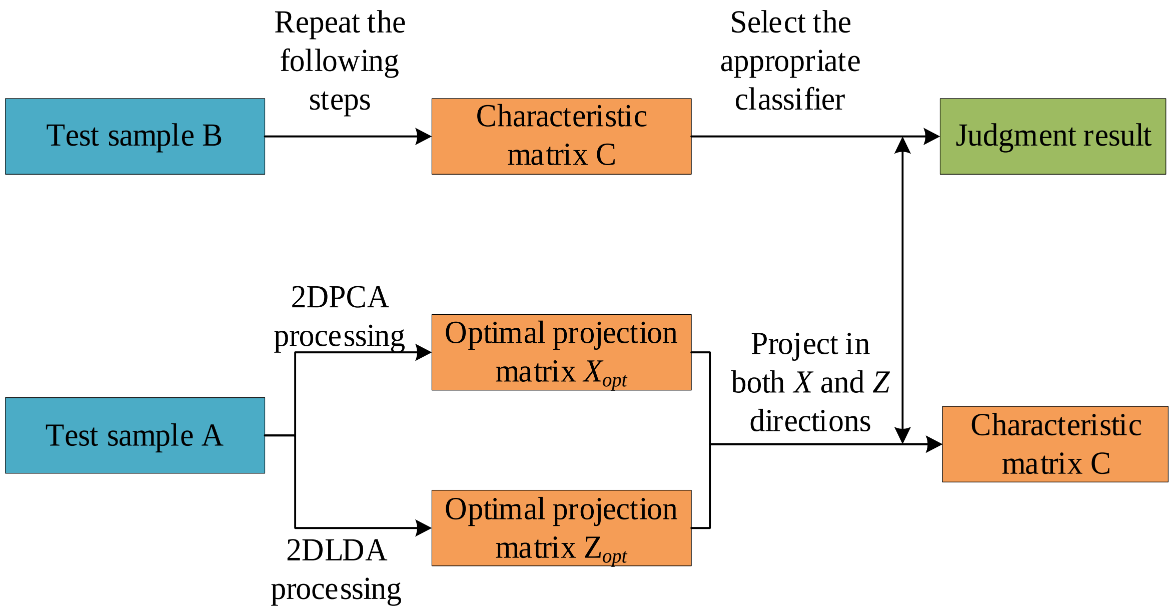


Fig. 3. T_2D_PL algorithm calculation flow chart.

As shown in Fig. 3, $m \times n$ a face image sample of size 1 is A subjected to two-dimensional PCA transformation in the row direction and two-dimensional LDDA transformation in the column direction, thereby outputting the optimal projections in the two directions X_{opt}, Z_{opt}, and then according to the two optimal projections matrix to form a feature matrix C. Projection dimension reduction B will be performed according to the optimal projection to obtain a reduced dimension matrix A. After repeating the above operations, the face image data with an appropriate dimension reduction can be output. Note that the calculation method of the feature matrix C is shown in formula (6).

$$C = Z_{opt}^{T} A X_{opt} \tag{6}$$

Finally, the nearest neighbor classifier is used to calculate the Euclidean distance between the two C and the k sub-processed feature matrix C_k to complete the classification of the input data. The calculation method of the Euclidean distance between the two is shown in formula (7).

$$D(C, C_k) = \sum_{i=1}^{q}\sum_{j=1}^{d}\sqrt{\left(C^{(i,j)} - C_k^{(i,j)}\right)^2} \tag{7}$$

Where q and d are the number of eigenvectors selected in multiple directions, respectively. So far, the data dimensionality reduction algorithm applied to the library face recognition book return model has been constructed.

B. Design of Improved Nonlinear Feature Extraction Algorithm based on Fusion Kernel Function

At the same time, performing two-dimensional PCA processing on the horizontal direction of the pixel matrix of the image data and two-dimensional LDA processing on the vertical direction of the pixel matrix can effectively reduce the dimension and compress the image on the premise of retaining the core information of the original image as much as possible. However, the above methods are often used to process linear structural data, and the processing effect of nonlinear image data is not good. Therefore, in this study, referring to the idea of kernel function, a feature extraction method of face image data combining T_2D_PL algorithm and combined kernel function is proposed and the recognition algorithm (hereinafter referred to as improved T_2D_PL algorithm). In the improved T_2D_PL algorithm, a kernel function is introduced to deal with the non-linear data brought by facial expression, facial posture, lighting environment and other conditions, which have a negative impact on face recognition. The data processing principle of the kernel function is shown in Fig. 4.

It can be seen that for nonlinear data, it may not be possible to find an identification plane that can clearly distinguish it in the plane, because it has the property of linear inseparability, so it needs to be mapped to three or more dimensions to find a suitable dividing plane. In the algorithm, the T_2D_PL method is still used to reduce the dimensionality of the face data, which is used to delete redundant information and improve the accuracy and speed of subsequent face recognition; column-wise feature extraction and face recognition. Since the data is mapped into a more dimensional feature space by the combined kernel function, the overall time complexity of the algorithm is significantly increased, so the algorithm needs to reserve more storage space and time for data calculation when running. The following is a detailed design of the combined kernel function in the improved T_2D_PL algorithm and the calculation flow of the algorithm.

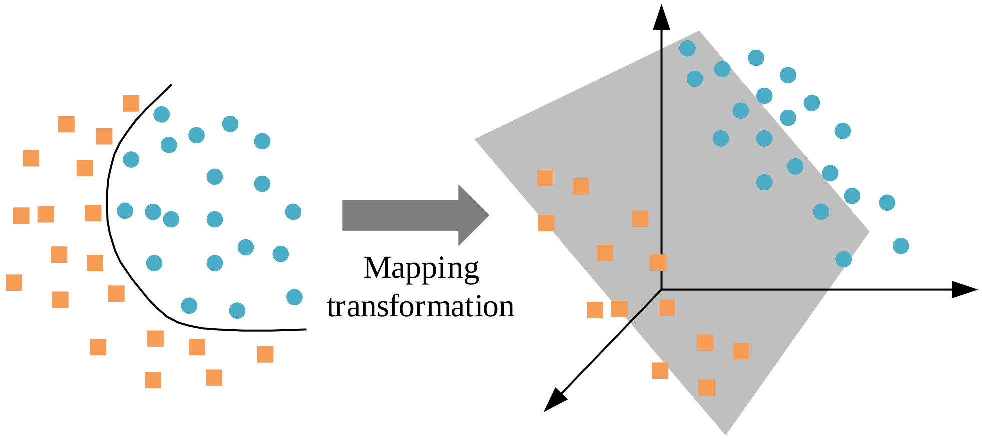


Fig. 4. The schematic diagram of the kernel function mapping processing data.

Different types of combined kernel functions will lead to different applicable objects and different sensitivity to different data processing. Specifically, the local kernel function can process local information accurately and efficiently. The global kernel function is more suitable for extracting global data information and has stronger generalization ability. For example, the Gaussian kernel function is a commonly used local kernel function. When the parameter increases, its extrapolation ability will gradually weaken, and the global data processing ability of the polynomial kernel function is better, which belongs to the global kernel function. Since the selection of the kernel function will directly affect the final recognition performance of the model, this study adopts the idea of combining kernel functions to construct the calculation kernel function in the algorithm. Specifically, it refers to a reasonable linear combination of various types of kernel functions by judging different processing requirements, so as to achieve the premise of retaining the overall information of the data, highlight the local features from different face image categories, and output more excellent judgment results. In this study, the optimal parameter combination of various single kernel functions was first tested experimentally, and then the search center was used to determine the optimal combination of kernel function parameters by grid search method, so that various weight coefficients could be tried in the future., to obtain the best recognition effect. The specific calculation steps of the improved T_2D_PL algorithm have four steps. The first is to map the dimensionality-reduced dataset to the multi-dimensional feature space using the combined kernel function. Assume that the processed input face dataset is $X=\left[X_1,X_2,...,X_M\right]$, and $X_i=\left[\left(X_i^1\right)^T,\left(X_i^2\right)^T,...,\left(X_i^m\right)^T\right]^T$ the kernel matrix K of size, $\left(i\times k, j\times l\right)$ can be calculated using Equation (8).

$$K=\Psi\left(X_i^k\right)\cdot\Psi\left(X_j^l\right)=\Psi\left(X_i^k\right)\cdot\Psi\left(X_j^l\right)^T \quad (8)$$

Eq. (8) $\Psi()$ represents the combined kernel function, which represents X_i^k the j row vector of the k image sample, X_i and l is the shape parameter of the kernel matrix. The second step is to use Eq. (9) to calculate the eigenvalues and eigenvectors of the kernel matrix.

$$Kb=b\hat{\lambda} \quad (9)$$

In Eq. (9), $\hat{\lambda}$ is the largest eigenvalue obtained by decomposing the kernel matrix, from which the previous p largest eigenvalue in descending order is selected as the eigenvector of the kernel matrix b. Then, the kernel matrix that has been mapped to the high-dimensional feature space is centered, and the feature vector $V^{(i)}$ can be calculated using Eq. (10).

$$V^{(i)}\cdot V^{(i)}=1 \quad (10)$$

In formula (10) $i\in 1,2,...,p$. Finally, extract the principal components of the row vector of the sample, and obtain the matrix after the row vector is projected by the eigenvectors in the high-dimensional kernel space. $Y_l^{(i)}$ The calculation method is shown in formula (11),

$$Y_l^{(i)}=\sum_{j=1}^{M}\sum_{k=1}^{n}\frac{\alpha_{(j-1)n+k}^{(i)}}{\sqrt{\hat{\lambda}^{(i)}}}K(X_i^l,X_j^k) \quad (11)$$

Where the first $\hat{\lambda}^{(i)}$ feature α is in the largest feature set, and i is the known mapping parameter. From this, a matrix of Y_t size can be obtained $m\times p$, and its calculation method is shown in formula (12).

$$Y_t=\left[Y_t^{(1)},Y_t^{(2)},...,Y_t^{(p)}\right] \quad (12)$$

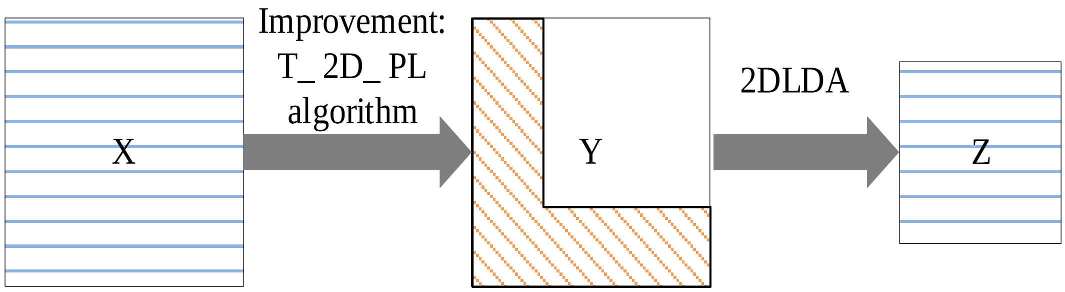


Fig. 5. Data dimensionality reduction process of T_2D_PL method.

After using the improved T_2D_PL algorithm to compress the row and column bidirectional information of the sample, the feature matrix can be obtained Y, and then the matrix is subjected to two-dimensional linear discriminant analysis (2DLDA), that is, through the classification, information of the data itself is subjected to secondary dimensionality reduction and compression, and its specific dimensionality reduction process is shown in Fig. 5.

The process shown in Fig. 5 will be explained in detail below. It is assumed that the total number of images to be processed is M the number of M_i Y_k samples in the training sample of the first category. There are C two i categories $Y_j^{(i)}$ in the j image data Y_k. k A sample matrix, $\bar{Y}^{(i)}$, $\bar{Y}$ respectively represent i the mean image information of the first-class sample and the mean matrix of all sample images, and there is the relationship of formula (13).

$$\bar{Y} = \frac{\sum_{i=1}^{M} Y_i}{M} \tag{13}$$

Assuming that Y is the size $m \times p$ of the image data to be tested, after mapping it to the W direction, it will form a matrix Z, and its size is $d \times p$ (d □ m), then the average inter-class distance of the image data after the projection can be calculated according to formula (14).

$$H_b = \left[\sum_{i=1}^{c} M_i \left(\bar{Y}^{(i)} - \bar{Y} \right) \left(\bar{Y}^{(i)} - \bar{Y} \right)^T \right] / M \tag{14}$$

The average intra-class distance after projection can be obtained by formula (15).

$$H_w = \sum_{i=1}^{c} \sum_{j=1}^{M} \left(\bar{Y}_j^{(i)} - \bar{Y}^{(i)} \right) \left(\bar{Y}_j^{(i)} - \bar{Y}^{(i)} \right)^T / M \tag{15}$$

Therefore, the Fisher criterion function after projection can be expressed by Eq. (16).

$$J(Z) = \frac{W^T H_b W}{W^T H_w W} \tag{16}$$

Finally, the matrix is calculated $H_w^{-1} H_b$, and the previous largest eigenvalue in descending order d and the corresponding orthogonal eigenvector are selected to $w_1, w_2, \ldots, w_d$ form the optimal projection space of the image, which is expressed by formula (17).

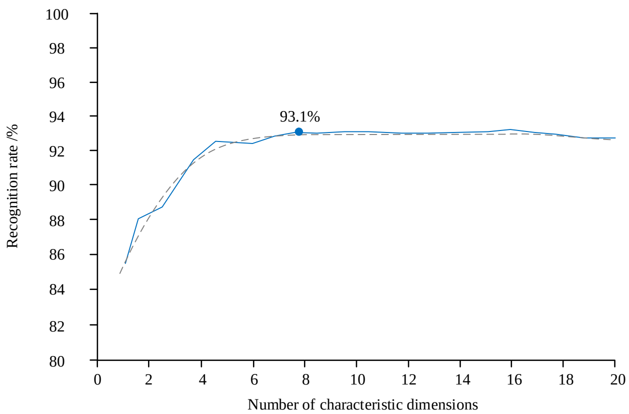
$$W = \left[w_1, w_2, \ldots, w_d \right] \tag{17}$$

That is to say, after the improved T_2D_PL algorithm dimensionality reduction processing, a dimensionality $d \times p$ reduction matrix of size can be obtained to represent the judgment result of the algorithm on the input data, and the calculation formula is shown in formula (18).

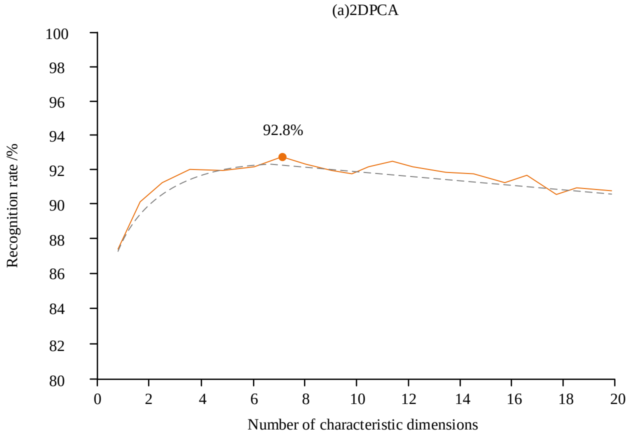
$$Z = W^T Y \tag{18}$$

IV. Library Face Book Return Model Performance Test

Before putting it into a practical environment, it is necessary to test the practical performance of the model. The test core of the face-returning-book model is the face recognition ability of the algorithm that composes the model. Therefore, the improved T_2D_PL algorithm is designed in this study (hereinafter referred to as the XT_2D_PL algorithm). For the test, the data selected for the test came from 200 people from many domestic colleges and universities. Each person was photographed with 12 face images with different postures and expressions, and the image type was 112×92 a grayscale image. In the test experiment, the recognition rate and calculation time are selected as the evaluation indicators for the quality of face recognition results. To compare the relative performance of the designed algorithms, two-dimensional LDA, two-dimensional PCA, T_2D_PL algorithm, and VGG neural network algorithm are selected as comparison methods. The parameters of the two-dimensional LDA model include the number of topics, the number of iterations, and the overfitting coefficient; The two-dimensional PCA model has parameters such as target dimensionality reduction quantity and whether to perform whitening treatment; T_ 2D_ the parameters of PL and its derived algorithms are all the parameters of the two-dimensional LDA model and the two-dimensional PCA model; The parameters of VGG neural network mainly include the number of neurons in each layer, the type of activation function and objective function, and the parameter initialization mode. These parameters are determined by combining industry experience and usage practices, and conducting experiments by repeatedly debugging and selecting the model with the best testing results. First, analyze the face recognition rate of 2D LDA and 2D PCA under the condition of different number of features, as shown in Fig. 6.



(a)2DPCA



(b)2DLDA

Fig. 6. Statistics of face recognition rate of 2D LDA and 2D PCA under different number of features.

In Fig. 6, “2DPCA” and “2DLDA” represent two-dimensional principal component analysis and two-dimensional linear discriminant analysis, respectively. The gray dotted line in the figure is the fitting trend line of the characteristic curve, that is, Fig. 6[(a), (b)] represents the statistical graphs of the face recognition rate curves under different numbers of features obtained by using the 2DPCA and 2DLDA methods for face recognition processing. Observing Fig. 6, it can be seen that as the number of features of the image to be processed increases, the face recognition rate of the 2DPCA algorithm first increases and then tends to converge, and the 2DLDA first increases rapidly and then slowly decreases. When the number of feature dimensions of the 2DPCA and 2DLDA methods reaches 8 and 7, respectively, the recognition rate reaches the maximum value of 93.1% and 92.8%. The following analyzes the algorithm recognition rate when the T_2D_PL algorithm is used alone, and the number of PCA and LDA feature dimensions in the algorithm takes different combination schemes. The statistical results are shown in Table I.

Observing Table I, it can be seen that when the dimension of the linear discriminant is fixed and the dimension of the PCA feature is increased, or when the dimension of the PCA feature is fixed and the linear discriminant feature is increased, the change rule of the recognition rate is roughly the same as that in Fig. 6, both of which show a rapid growth first and then are steady and slightly down. When the PCA feature dimension and the linear discriminant feature dimension of the T_2D_PL algorithm are both 12, the recognition rate reaches the maximum value of 94.4%. Next, we will analyze the recognition rate of each algorithm when the number of samples under each type of face samples is different. The statistical results are shown in Fig. 7.

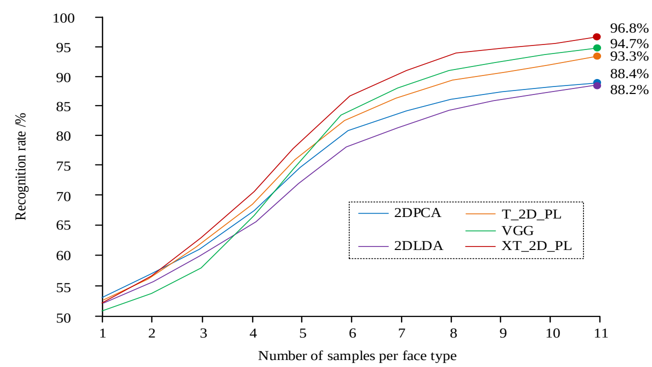


Fig. 7. The face recognition rate statistics of the algorithm under different sample numbers of each type.

TABLE I. RECOGNITION RATE STATISTICS OF T_2D_PL ALGORITHM UNDER DIFFERENT FEATURE DIMENSION NUMBER SCHEMES (UNIT: %)

PCA feature dimension	Linear discriminant feature dimension						
	3	6	9	12	15	18	21
3	64.3	77.8	81.2	80.3	81.9	81.2	80.7
6	85.2	90.9	91.0	89.5	90.2	88.3	90.5
9	88.0	90.7	91.9	90.2	90.8	89.5	90.2
12	89.2	91.8	92.8	94.4	89.7	91.4	91.3
15	89.7	91.9	92.8	93.9	91.7	91.6	90.6
18	90.1	92.4	93.2	93.7	91.2	90.9	90.2
21	89.7	92.0	92.1	93.4	90.8	90.3	90.0

The horizontal axis in Fig. 7 is used to describe the number of samples for each type of facial image in the sample to be processed, the vertical axis represents recognition rate, and different line colors represent different recognition algorithms. Observing Fig. 7, it can be seen that the trend of the recognition rate change curve of each face recognition method is generally consistent with the increase of the number of face samples in each class. When the number of face samples in each class is less than 5, the recognition rate of each recognition model increases rapidly as the number of face samples in each class increases. However, when the number of face samples in each class is 5, the recognition rate growth curve of each model basically reaches a turning point. Subsequently, the number of facial samples in each category continued to increase, and the growth rate of facial recognition rates in each model gradually slowed down, reaching its maximum value when the number reached 11. Specifically, when the number of samples for each type of face is 11, the face recognition rates of the 2DLDA, 2DPCA, T_2D_PL, VGG, XT_2D_PL algorithms are 88.2%, 88.4%, 93.3%, 94.7%, and 96.8%, respectively. When the number of face samples is small, the face recognition rate of each algorithm has a small gap, and the recognition rate of the VGG algorithm is the lowest. This is because VGG belongs to a neural network algorithm and requires a high amount of training data and diversity. Therefore, In this case, a good application effect cannot be obtained. When the number of face samples of each type is large, the recognition performance of the VGG algorithm is significantly improved, and the recognition rate is only lower than the XT_2D_PL algorithm designed in this study. Therefore, the VGG algorithm and the XT_2D_PL algorithm are grouped into a group below, and they remain in the same group with the algorithm, and the changes of their recognition rate with the feature dimension are grouped and counted. The statistical results are shown in Fig. 8.

Assuming that the number of feature dimensions in Fig. 8 is a variable x, the feature dimension parameters of the T_2D_PL algorithm are taken in the row and column directions (x, x), and the feature dimension parameters of the XT_2D_PL algorithm have the best recognition effect after multiple debugging $(x, x-3)$. Observing Fig. 8, it can be seen that VGG and XT_ 2D_ The change pattern of facial recognition rate curve of PL algorithm is significantly different from other algorithms in different feature dimensions. VGG and XT_ 2D_ There is a significant overall positive correlation between the recognition rate of the PL algorithm and the number of feature dimensions, but in other algorithms, only when the number of feature dimensions is less than 8, there is a certain positive correlation between the recognition rate and the number of feature dimensions. After the number of feature dimensions is greater than 8, there is no significant increase in the recognition rate of each algorithm's face. With the increase in the number of feature dimensions, T performs dimensionality reduction in both column and column directions_ 2D_ The face recognition rate of PL algorithm is significantly higher than that of using only 2DLDA algorithm or 2DPCA algorithm, because the former has more dimensionality reduction directions and can retain more original image information. Observing in Fig. 8(b), it is found that when the number of feature dimensions is less than 4, the recognition rates of the VGG algorithm and the XT_2D_PL algorithm are both low, but increase rapidly. When the number of feature dimensions exceeds 14, the face recognition of both exceeds that of the other three algorithms, and the highest face recognition rates of the two are 95.4% and 96.3%, respectively. Finally, the computational efficiency of each algorithm is compared, and the computational time-consuming evaluation under different computational sample sizes is used. The statistical results are shown in Fig. 9.

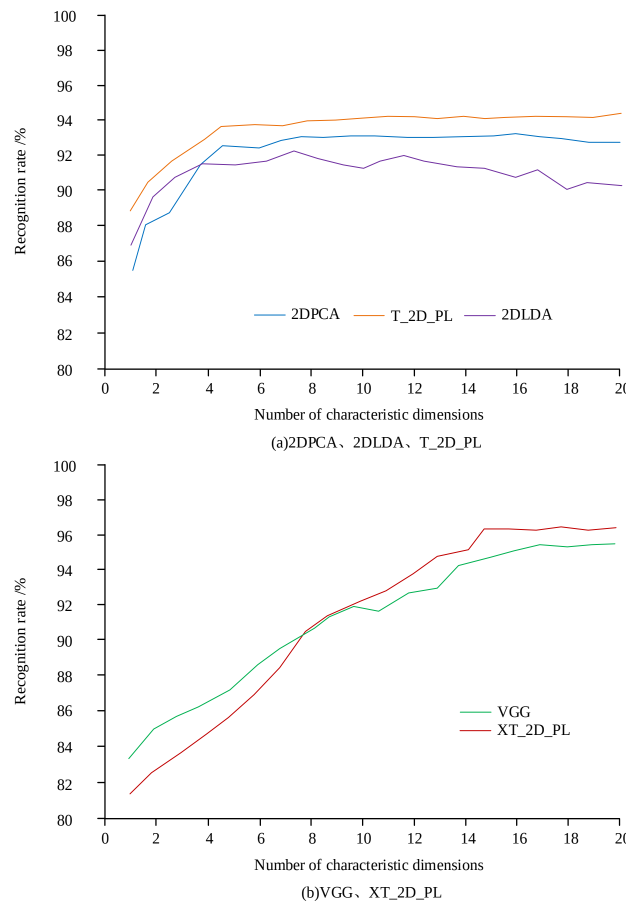


Fig. 8. Statistics of face recognition rate of each algorithm under different feature dimensions.

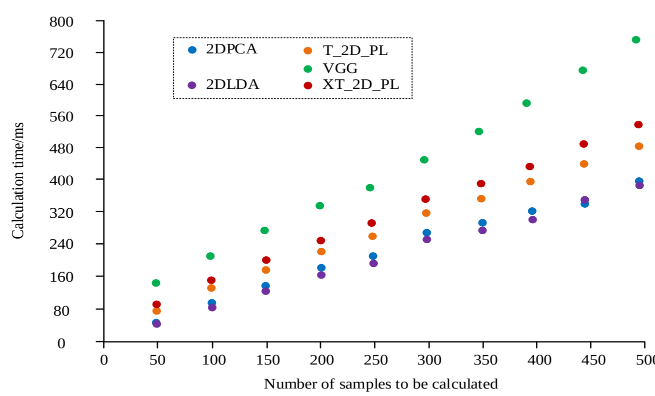


Fig. 9. The calculation of time-consuming statistics of each algorithm under different calculation samples.

The horizontal axis in Fig. 9 is used to describe the number of samples to be detected in each experiment, and the vertical axis is the calculation time of each algorithm, and the unit is ms. Analysis of Fig. 9 shows that, as a whole, with the increase of the data to be detected, the calculation time of each algorithm increases linearly, and the calculation time of the 2DLDA algorithm or the 2DPCA algorithm under various experimental schemes is significantly lower than that of other algorithms. The algorithm, mainly because it has the smallest algorithm complexity requires the fewest computational steps. The calculation time of the XT_2D_PL algorithm and the T_2D_PL algorithm is higher than the first two algorithms, and the calculation time of the XT_2D_PL algorithm is better. The calculation time of the VGG algorithm is the highest among all the experimental schemes. A large number of processing steps are required before outputting the recognition results. When the number of samples to be processed is 500 images, the computation time of 2DLDA, 2DPCA, T_2D_PL, XT_2D_PL, and VGG algorithms are 391ms, 395ms, 481ms, 536ms, and 754ms, respectively, and the calculation speed is 0.782ms/per photo, 0.79ms/per photo, 0.962ms/per photo, 1.072ms/per photo, 1.508ms/per photo. Although the face recognition speed of the library face return mode based on the XT_2D_PL algorithm is not the fastest, the calculation speed is enough to satisfy the library staff Facebook's needs.

V. Conclusion

The daily book return behavior of the university library occurs frequently, and a reasonably designed intelligent book return system can help improve the efficiency of the university library and save time for the majority of teachers and students on campus. In this study, the XT_2D_PL algorithm was constructed by using the kernel function and multi-dimensional principal component analysis method, and it was applied to the face recognition work in the library intelligent return system. The experimental results of the algorithm performance test show that the changing trend of the recognition rate change curve of each face recognition algorithm with the increase of the number of face samples of each type is roughly the same, and the growth rate is accelerated first, then the growth rate is greatly reduced and finally stabilized within a certain range of values. When the number of samples for each type of face is 11, the face recognition rates of the 2DLDA, 2DPCA, T_2D_PL, VGG, and XT_2D_PL algorithms are 88.2%, 88.4%, 93.3%, 94.7%, and 96.8%, respectively. When the number of feature dimensions is less than 4, the recognition rates of the VGG algorithm and the XT_2D_PL algorithm are both low, but grow rapidly. When the number of feature dimensions exceeds 14, the face recognition rates of the two algorithms exceed those of the other three algorithms, and the face recognition rates are 95.4% and 96.3%, respectively. When the sample to be processed is 500 pictures, the calculation speed of 2DLDA, 2DPCA, T_2D_PL, XT_2D_PL, VGG algorithm is 0.782ms/per photo, 0.79ms/per photo, 0.962ms/per photo, 1.072ms/per photo, 1.508ms /per photo. The experimental data proves that the library face-to-book model based on the XT_2D_PL algorithm designed in this research has high face recognition accuracy, and the recognition speed meets the application requirements.

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