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# Face Recognition Implementation Based on Improved Principal Component Analysis

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***Abstract***— *In recent years, face recognition, as a research topic with both theoretical and application values, has been receiving more and more attention from various scholars. The so-called Face Recognition is a technology that uses computer to analyze the face image and extract effective recognition information from it to identify the identity. In other words, after standardizing a known face, it is matched with the face specimen in the database by some method to find the corresponding face and the information related to the face in the database. In this paper, we first give an overview of face recognition, and propose the concept of face recognition, the content of face recognition, including face detection, feature extraction and face recognition. Among them, feature extraction is the most important part, and Principal Components Analysis (PCA) algorithm is one of the most important methods in feature analysis. In the next paper, we analyze the PCA algorithm, theoretically analyze the PCA algorithm, and apply it to face recognition to obtain analytical results. Finally, some improvement ideas are proposed regarding the defects of PCA algorithm.*

***Keywords***— *Face recognition,feature extraction,Principal component analysis.*

## I. Introduction

With the development of society and the advancement of technology, especially the rapid development of computer technology in recent years, there is an increasingly urgent need for automatic identity verification in all aspects of society, and these identifications are expected to be fast and efficient. Biometric technology has gained great importance and development in the field of scientific research. Biometric features are the most ideal basis for identity verification because they are intrinsic properties of human beings, with strong self-stability and individual variability [1]. Among them, the use of facial features for identity verification is the most natural and direct means, and because facial recognition systems are more friendly, convenient, and easier to be accepted by users than other human biometric identification systems such as fingerprints, iris, palm prints, etc., they have a broader application area [2].

It is well known that face recognition is closely related to other biometric recognition methods and to the field of computer human-computer interaction. In addition, face recognition research involves knowledge from various fields, not to mention pattern recognition, image processing, computer vision and other related disciplines, but also from physiology, psychology and other cognitive sciences. Therefore, face recognition research is of great scientific significance for developing new technical fields and promoting interdisciplinary and comprehensive development. In addition, face recognition has become a key technology in computer vision and related fields, and there are already examples of applications that successfully integrate face recognition technology into the fields of identity verification, criminal investigation and crime solving, entrance control, video surveillance, robot intelligence and medicine. Therefore, face recognition also has broad application prospects and commercial value.

## II. Current Status of Research and Main Problems

The domestic research work is mainly focused on three major types of methods: geometric feature-based face frontal automatic recognition methods, algebraic feature-based face frontal automatic recognition methods and connection mechanism-based face frontal automatic recognition methods [5].

Since the 1980s, the research on face recognition has been started in China. The main research units in this area include Tsinghua University, Institute of Computing of Chinese Academy of Sciences, Institute of Automation of Chinese Academy of Sciences, Harbin Institute of Technology, Fudan University, University of Science and Technology Beijing, etc. All these research institutions have achieved more or less certain results. Not only the organizations have achieved good results, but also the individual researchers have made remarkable gains. Among them, Cheng Yongqing, Zhuang Yongming et al. performed SVD decomposition on the average gray map of similar images to obtain the feature face space, and the projection of each image on the feature face space as its algebraic features, and then used hierarchical discriminations to classify them. Peng Hui and Zhang Changshui further developed the "feature face" method by proposing to use the inter-class scattering matrix as the generation matrix, which further reduces the dimensionality of the generation matrix and greatly reduces the computation while maintaining the recognition rate. Zhou has implemented a frontal face recognition system with feedback mechanism, using integral projection method to extract the key points of facial features and use them for recognition, which has achieved satisfactory results. He also tried the "stable point-of-view" feature extraction method, i.e., in order to include 3D information in the recognition system, he did some research on face side silhouette recognition, and realized the recognition system with front and side cross-reference. Zhang Hui, Zhou Hongxiang, and He Zhenya used a symmetric principal analysis neural network to extract and recognize features of human faces using a combination of redundancy removal and weight orthogonality. The method uses a small amount of feature data and a small feature extraction operation, which achieves the storage of a large number of face samples and the fast recognition of faces relatively well. Professor Wang Zhiliang of University of Science and Technology Beijing focuses on artificial psychology and establishes a psychological model based on mathematical formulas [3].

Although face recognition technology has a broad application prospect, it still has a certain gap when compared with fingerprint, retina and other recognition methods which have a more accurate recognition rate. The reason is mainly due to the existence of some face graphics and other problems, which in turn reduce the recognition rate of face recognition.

## III. REALIZATION PROCESS

We know that a pair of images can be viewed as a matrix, and the elements in this matrix are the pixel values of the individual points in the image. But we can also extend it and see it as a vector, for example, an image with M*N pixels can be seen as a point in an M×N dimensional space of length, and this vector representation of the image is the original image space. But this space is only one of many spaces that can represent an image, which is the subspace for image detection. Regardless of the specific form of the subspace, the basic idea of their use for image recognition is the same, which is to first select a suitable subspace, then project the image onto this subspace, and then use some kind of metric between the images projected onto the subspace to determine the similarity between images, the most common being various distance metrics.

The PCA method was proposed by Turk and Pentlad, and it is based on the Karhunen-Loeve transform (K-L transform for short). It is a commonly used orthogonal transform. A detailed description of the K-L transform is first given below.

Suppose X is an n-dimensional random variable and X can be expressed as a weighted sum of n basis vectors.

$$X=\sum_{i=1}^{n}\alpha_i\varphi_i$$

where $\alpha_i$ is the weighting factor and $\varphi_i$ is the basis vector, this equation can also be expressed in matrix form as

$$X=(\varphi_{1,}\varphi_{2,}\cdots_{,}\varphi_{n,})(\alpha_{1,}\alpha_{2,}\cdots_{,}\alpha_{n,})^{T}$$

The basis vectors are taken to be orthogonal vectors. Since it consists of Φ orthogonal vectors, and Φ is an orthogonal matrix, so

$$\Phi^T\Phi=I$$

$$\alpha=\Phi^T X$$

Thus obtained.

$$\alpha=\Phi^T X$$

In summary, the coefficients of the K-L transformation expansion can be found by the following steps.

Step 1 Find the covariance matrix R of the attendant vector X.

Step 2 Derive the eigenvalues and eigenvectors of the covariance matrix R.

Step 3 Expanded coefficient i.e. $\alpha=\Phi^T X$

The essence of the K_L transform is to establish a new coordinate space and then orthogonal transform the original data. This transform removes the correlation between each component of the original data vector, and also removes those data that are not very informative, or are noisy or redundant, so as to achieve the effect of reducing the dimensionality of the feature space.

## IV. FACE RECOGNITION ALGORITHM

The complete PCA application in face recognition includes the following steps: face image preprocessing; reading into the face library; calculating the matrix using the K-L transform; calculating the eigenvalues and eigenvectors of the matrix to form the subspace; projecting the training and test images onto the obtained subspace; and selecting a certain distance function for recognition.

Since the specifications of various devices are different, the specifications of the images formed by these devices are also different, and the images that come to our hands are also different. For better recognition, it is necessary to pre-process these images to make their specifications uniform. Generally speaking, the steps of face image pre-processing are divided into three steps: geometric normalization, gray scale normalization and edge detection sharpening process.

The geometric normalization of the image is mainly to unify the relative positions of key parts of the human face, such as eyes, nose, mouth and other five senses in the image, in each face image. For those original images without any processing, the positions of the face parts in the images are shifted and not very uniform. So, if we use PCA and other face recognition methods based on overall gray scale statistics when performing face recognition, then it will have an impact on the correct recognition. Therefore, it is necessary to process the input images so that all the images of faces have the same size specification, and the pixel values are also unified, and preferably the key features in the faces are also unified.

Since the grayscale of the face image data acquired under different lighting conditions varies greatly, we have to normalize the grayscale of the image through preprocessing to remove the effect of lighting under certain conditions. There are many methods of grayscale normalization.

Edge detection of an image is to extract the demarcation line between the target and the background by detecting the location where the image characteristics change (e.g., the greatest change in gray scale). Sharpening of the image is to enhance the target boundary and image details in the image, to perform image enhancement by strengthening the contrast of the image, and to extract the contour of the image.

After normalizing the face library, a certain number of images are selected for each person in the library to form the training set and the rest to form the test set. In a computer, a pair of digital images can be viewed as a matrix or an array, denoted by B(i,j). The subscript of its row corresponds to a point on the image, and the corresponding element in the matrix bij marks the gray value of the point. A pair of n×m size images are connected by row to form an n*m dimensional vector

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$$X = (b_{11}, b_{12}, ..., b_{1m}, b_{21}, b_{22}, ...b_{2m}, ..., b_{n1}, b_{n2}, ..., b_{nm})$$

It can be considered as a point in an n*m dimensional space. This image can then be described by a low-dimensional subspace through the K-L transform.

The overall dispersion matrix of the training samples is used as the generation matrix, i.e.

$$\sum = E\{(x-\mu)(x-\mu)^T\}$$

That is, the covariance matrix of all training samples is

$$C_A = (A \bullet A^T) / M$$

where $A = \{\varphi_1, \varphi_2, ..., \varphi_M,\}$, M is the average number of faces, the covariance matrix CA is an N*N matrix, and N is the dimensionality.

According to the principle of K-L transformation, the new coordinate system sought consists of the eigenvectors corresponding to the nonzero eigenvalues of the matrix A.AT. It is difficult to find the eigenvalues and orthogonal normalized eigenvectors of matrix CA of size N*N directly, so the principle of singular value decomposition is introduced to obtain the eigenvalues and eigenvectors of $A \bullet A^T$ by solving the eigenvalues and eigenvectors of $A^T \bullet A$.

We obtained M feature vectors, and although M is much smaller than m, M is still large. In fact, not all the feature vectors, u, are to be retained according to the requirements of the application.

Each face image is projected into the feature face subspace to obtain a set of coordinate coefficients, which corresponds to a point in the subspace. Likewise, any point in the subspace corresponds to an image. This set of coefficients can then be used as the basis for face recognition, which is the characteristic face feature of this face image. In other words, any face image can be expressed as a linear combination of this set of feature faces, and the individual weighted coefficients are the expansion coefficients of the K to L transform.

Specifically, after computing all the non-zero eigenvalues $[\lambda_0, \lambda_1, ..., \lambda_{r-1}]$ (ordered from largest to smallest,1 $\leq$ r $\leq$ M) of $C_A$ and the corresponding unit eigenvectors $[u_0, u_1, ... u_{r-1}]$ , the feature space $U = [u_0, u_1, ..., u_{r-1}]$ can be obtained so that the projection coefficients of an image X on the feature space (which can also be interpreted as the coordinates of X in the space U) can be computed as follows.

$$X = UY \rightarrow Y = U^{-1}X = U^T X$$

Using the above formula for projection coefficients, all training images are first projected, and then the same projection is performed for the test images. After the images are projected into the feature subspace, the next step is to discriminate the similarity between images. There are usually two ways to discriminate the similarity between images: one is to calculate the distance between images in N-dimensional space, i.e., between points, and the other is to measure the similarity between images. When measuring the distance, we want the distance to be as small as possible, and generally choose the training image closest to the test image as the class it belongs to. When measuring similarity, we want the images to be as similar as possible, which means that the training image class with the greatest similarity is considered to be the class to which the test image belongs.

## V. Implementation and Results Analysis

This experiment uses color face images from the Essex face Database, a face recognition database at Essex University, UK. These images can all be considered as large headshots and are of the same size, all 180×200 pixels, 24-bit JPG images. Also they have a more uniform background, which is more conducive to the experiment. In the 20 images of the same person, the face size is basically the same and the lighting conditions are approximate, without strong light exposure. And the skin color of each person is closer.

Then 20 images of one of them are given, with subtle differences such as eyes and mouth between each image. The first 10 of these images are classified as training samples and the last 10 are classified as test samples.

The basic implementation of face recognition was changed in the program to obtain the analytical comparison results of the experiment. Since this study is focused on the algorithm itself, the program implementation is lacking. All comparative data are obtained manually and there is no comparison with other algorithms, which is lacking in the program itself, but does not prevent the experimental results from being obtained.

If no comparative study is performed, the program selects any ten people from the face pool with 20 images each for testing. Where each person selects their respective ten images as a training sample and the remaining ten images as a test sample. After running the program, an input prompt will appear. For the convenience of input, the images have been numbered 1, 2, 3, ... and so on. After the number is entered, the program will run and the test image corresponding to that number will appear, as well as the image corresponding to the training sample for recognition, and the number corresponding to the age of the training image that appears on the screen.

Putting different numbers of faces in the training sample with the same number of dimensions yields the results shown in the following table.

TABLE I: Relationship between the number of images and recognition rate

| **Training pictures n** | 10 | 9 | 8 | 7 | 6 |
|---|---|---|---|---|---|
| **Recognition rate** | 0.90 | 0.88 | 0.86 | 0.85 | 0.85 |

From the data in the table, it can be found that the higher the number of training samples, the higher the recognition rate for the same number of subspace dimensions. This is in accordance with the probabilistic statistics: the better the training preparation, the better the recognition.

Determine the same sample space for each of the 10 frames at the beginning and pick a different number of dimensions for the experiment. Selecting different number of dimensions also means selecting different number of eigenvalues, and the way to achieve this in the program is to change the values compared with the eigenvalues. The original value is 1, and gradually increasing the limited value, the results are obtained as shown in the following table.



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TABLE II: Relationship between different subspace dimensions and recognition rate

| **Numerical value** | 1 | 1.2 | 1.5 | 1.8 | 2 |
|---|---|---|---|---|---|
| **Recognition rate** | 0.89 | 0.88 | 0.87 | 0.88 | 0.88 |

From the above table, we can find that the recognition rate does not increase with lower values and more dimensions of subspace, but decreases when the value increases from 1 to 1.5 dimensions; however, the recognition rate starts to increase again when the value continues to increase and the dimension of subspace decreases. It can be assumed that some feature vectors may contain information unrelated to the face, such as the background, which may cause the instability of recognition rate.

We can choose different distance functions for face identification in the final face identification. The previously mentioned Euclidean distance and minimum distance are selected for comparative study and the results are obtained as shown in the following table.

TABLE III: Relationship between different distance functions and recognition rate

| **Distance function** | **European distance** | **Minimum Distance** |
|---|---|---|
| **Recognition rate** | 0.90 | 0.90 |

From the data in the above table, it can be seen that there is almost no difference in the recognition rate of PCA algorithm under the action of Euclidean distance and minimum distance functions. One of the reasons may be that these two distance functions have some similarity, so no matter which function is used, it will not have much effect on the final recognition rate.

## VI. SUMMARY

Face recognition is mainly composed of three parts: face detection, feature extraction and face identification, among which feature extraction can be said to be the most important. Whether the extracted face features can well reveal the essential information in the original face samples largely affects the merits of the whole face recognition system. In this paper, we mainly study the application of PCA in face recognition by analyzing PCA algorithm, i.e., extracting face image features and forming PCA face feature space. It not only represents the face well, but also achieves a good identification effect in the end. The traditional PCA method only makes use of the second-order statistical properties among the features, so this paper puts forward a little improvement idea for the shortcomings of the traditional PCA, and proposes an improvement idea for its influence in different lighting, different face expressions and different face poses. However, face recognition is not perfect under today's conditions, and face recognition should be further improved, such as effective expression of faces under the smallest possible constraints, fast and accurate recognition of faces even in complex backgrounds, etc. These are all challenging research efforts in the process of human recognition nowadays.

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