Design of Face QR Code Recognition System based on PCA

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Abstract. This article discusses the face two-dimensional code recognition technology, using the PCA algorithm to study the dimensionality reduction processing process of the face image. Based on the analysis of QR encoding and decoding methods, the generation of face two-dimensional codes is realized. Choose 140 pictures in ORL face database as the experimental data set, study the face two-dimensional code recognition system, and realize a process of face recognition. The experimental results show that the face image data has a large dimension, and the principal component analysis method can be used to obtain the key data. Through the experiment, PCA can be used to reduce the dimensionality to obtain the effective information of the face, and to encode and decode the two-dimensional code. The ZXing two-dimensional code open source library called by the experiment has high experimental efficiency, which is beneficial to improve the operating efficiency of face two-dimensional code recognition and facilitate the machine to complete the simulation.

1. Introduction

Biometric identification technology is a technology that uses the fusion of biotechnology and computer technology to determine a person's physical characteristics, thereby performing identity authentication [1]. Nowadays, in the field of biometric recognition technology, fingerprint recognition is the largest proportion, followed by other methods such as face recognition. In a high-level security environment, multiple technologies will be integrated to identify identity. With the emergence of more and more high-tech, many identity authentication requirements for technical functions are increasing. Today’s identity authentication systems prefer a variety of identity authentication and identification technologies, such as ‘password combined with biological characteristics’, ‘smart card combined with biological Features’ and so on. Facial recognition technology is now more and more close to the public’s vision. For example, the public security department conducts face authentication and fingerprint authentication in the ID card of the population’s household registration files. Criminal investigation departments can use biometric recognition technology to capture on-site snapshots or monitoring. The identity features of criminal suspects, and the extracted facial features are applied to the suspect database, speeding up the case-handling process. The most closely related to most people are the face recognition visitor system and the face recognition attendance system[2]. At the beginning, the QR code was mainly used in the field of automobile manufacturers, and its purpose was to track various parts of automobiles. Nowadays, mobile smart terminal devices have become popular, and many payment software have QR code recognition, which also popularizes the application of QR codes.
2. PCA algorithm principle

2.1 K-L Mathematical Principle

K-L transformation, namely Karhunen-Loeve transformation, is a relatively common feature extraction method, which can keep the principal elements of the original information and disperse as much as possible so that there is no redundant information after processing. In data expression and computer learning, a set of data can be abstractly expressed as a set of vectors. General data can be expressed as column vectors, and a set of bases needs to be determined when describing. The geometric meaning of vector multiplication can be expressed as the scalar length of the projection of one set of vectors on another set of vectors, and the form of matrix multiplication can generally be used to replace the form of multiplication of two sets of vectors.

For two five-dimensional vectors, you can first arrange the five-dimensional vector into a five-row two-column matrix by column, and then multiply the changed matrix by a "base matrix" to get the value represented under the new base. The general representation of vector matrix is shown in formula 1.

\[
\begin{pmatrix}
  p_1 \\
  p_2 \\
  \vdots \\
  p_n
\end{pmatrix}
\begin{pmatrix}
  a_1 & a_2 & \cdots & a_m
\end{pmatrix}
= 
\begin{pmatrix}
  p_1a_1 & p_1a_2 & \cdots & p_1a_m \\
  p_2a_1 & p_2a_2 & \cdots & p_2a_m \\
  \vdots & \vdots & \ddots & \vdots \\
  p_na_1 & p_na_2 & \cdots & p_na_m
\end{pmatrix}
\tag{1}
\]

The above formula can be expressed as the multiplication of two matrices, that is, each column vector in the right a matrix is changed into a space based on each row vector of the left matrix. In fact, it represents a linear transformation.

From the above calculation, it can be known that if the value of M is less than R, the dimensionality of the original data can be reduced. So far we need to find a set of optimized basis.

2.1.1. Covariance matrix. If a set of two-dimensional data is reduced to one-dimensional data and the original information is not lost as much as possible, one of the most intuitive methods in the Cartesian coordinate system is to project, and habitually project all of them to the X axis and hope The more scattered the projected values are, the better, because if there are values overlapping, the sample information will disappear. The degree of dispersion of values can be expressed by mathematical variance. The variance formula is shown in formula 2.

\[
\text{Var}(a) = \frac{1}{m} \sum_{i=1}^{m} (a_i - u)^2
\tag{2}
\]

In one-dimensional data, variance can be used to express the degree of dispersion, and the larger the better. High-dimensional data needs to be constrained by covariance. Covariance can express the linear correlation of two variables, and it is hoped that they are orthogonal, because correlation means that the two variables are not completely independent [3]. The covariance formula is shown in formula 3.

\[
\text{Cov}(a,b) = \frac{1}{m} \sum_{i=1}^{m} (a_i - u_a)(b_i - u_b)
\tag{3}
\]

For the convenience of processing, set the mean value to 0, and the processing result is shown in formula 4.

\[
\text{Cov}(a,b) = \frac{1}{m} \sum_{i=1}^{m} a_ib_i
\tag{4}
\]

If only the two parameters a and b appear, they can be formed into a matrix X, and the result is shown in formula 5.

\[
X = \begin{pmatrix}
  a_1 & \cdots & a_m \\
  b_1 & \cdots & b_m
\end{pmatrix}
\tag{5}
\]

The above-mentioned matrix X covariance expansion is shown in formula 6.
So far this matrix contains the variance of the two variables and the covariance of the two variables. It can be intuitively found that they are placed on an orthogonal diagonal. And the value in the first row and two columns is the same as the value in the second row and one column[4].

$$\frac{1}{m} XX^T = \begin{pmatrix} \frac{1}{m} \sum_{i=1}^{m} a_i^2 & \frac{1}{m} \sum_{i=1}^{m} a_i b_i \\ \frac{1}{m} \sum_{i=1}^{m} a_i b_i & \frac{1}{m} \sum_{i=1}^{m} b_i^2 \end{pmatrix} = \begin{pmatrix} \text{Cov}(a,a) & \text{Cov}(a,b) \\ \text{Cov}(b,a) & \text{Cov}(b,b) \end{pmatrix}$$

(6)

2.1.2. Matrix diagonalization. Because it is necessary to increase the variance of the variables as much as possible and the data does not overlap, the other elements except the diagonal should be reduced to 0 and arranged from top to bottom, so as to achieve the purpose of optimization.

There are m n-dimensional data records arranged in matrix form X. Suppose $C = \frac{1}{m} XX^T$ is a symmetric matrix, the diagonal corresponds to the variance of each variable, and the nth row and m column are the same as the m row and n column, and the corresponding covariance matrix is C. P is a set of matrices composed by rows, and it is also a one-dimensional matrix after optimization. Set $Y=PX$, then Y is the data after X performs base transformation on P, that is, the data after dimensionality reduction. Suppose the covariance matrix of Y is D, and the derivation process is shown in formula 7.

$$D = \frac{1}{m} YY^T = \frac{1}{m} (PX)(PX)^T = P(\frac{1}{m} XX^T)P^T = PCP^T$$

(7)

So far, it can be seen that P is the final goal, and satisfying $PCP^T$ is a diagonal matrix. If the first j rows of data in the matrix P are multiplied by the target matrix X, the n-dimensional data in the X matrix can be reduced to j dimensions.

From the above discussion, we can see that C is a symmetric matrix, and the eigenvectors corresponding to different eigenvalues are linearly independent. Let matrix $E = (i_1, i_2, \ldots, i_n)^T$ and $i$ be the eigenvectors, and multiply the symmetric matrix C with it to complete its diagonalization. The result of the diagonalization is shown in formula 8.

$$E^T CE = \Lambda = \begin{pmatrix} \lambda_1 & & \\ & \lambda_2 & \\ & & \lambda_n \end{pmatrix}$$

(8)

Where Λ is a diagonal matrix, and its diagonal element $\lambda$ is the eigenvalue corresponding to each eigenvector in the E matrix. For the matrix P as shown in formula 9.

$$P = E^T$$

(9)

P is a matrix formed by unitizing the eigenvectors of the covariance matrix and arranging them in rows. If P is arranged from top to bottom according to the eigenvalues in Λ, the matrix composed of P and the original matrix X can be multiplied to obtain the optimized matrix Y.

It can be seen that these correlated data can be transformed by K-L, which makes the compressed data independent of each other while preserving the main information[5].

2.2. Eigenvalue selection

Although the data after the K-L transformation is reduced, they are not related to each other. Therefore, the K-L transformation still retains the important characteristics of the vector and achieves the purpose of reducing the dimensionality. The purpose of reducing the dimensionality is actually to reduce the amount of calculation and save the running time of the computer. K-L transformation can not only reduce the dimensionality, but also retain the main features and remove minor things. The following describes the feature extraction method in general:

1. In the case of preserving non-zero feature values, constructing the unprocessed face space only needs to use the feature vector corresponding to the feature value to construct the feature face.

2. In the case where only zero feature values are preserved, constructing the unprocessed face space can only use feature vectors corresponding to zero values to construct the feature face.
(2) Remove about 40% of the secondary eigenvalues, which can effectively reduce the dimensionality and improve the computational efficiency.

(3) Under normal circumstances, $\beta$ is greater than 90% and less than 1, which can ensure that too much data is not lost. The formula is shown in formula 10.

$$\beta = \frac{\sum \lambda_j}{\sum \lambda_k} = \mu_{k < N}$$

In the above formula, $\lambda_j$ is the eigenvalue of the matrix, and $\beta$ is the variance contribution rate.

3. Face QR code recognition

If a face image with a dimension of 300x300 is subjected to matrix quantization, the original feature value of 90,000 dimensions will eventually be obtained. Such a large operating capacity will greatly reduce the computing efficiency and cause a burden on the later classifier. If the principal component analysis algorithm is used to perform corresponding dimensionality reduction to obtain the corresponding low-dimensional subspace, the success rate of face recognition is improved compared with before.

3.1 Construct eigenface space

After a certain preprocessing, it is loaded into the ORL face database. This process completes the basic preprocessing and quantization of the image in advance, and the training forms a certain feature subspace. Put the trained image and the image to be recognized into the same feature subspace, and finally determine whether the image to be tested is of the same type as the trained face image by distance and length. For example, if there are j pictures to be trained, first unify each picture to the same size, then convert it into an n-dimensional vector to become a row vector, and then stack the row matrices together to form a large matrix $Y$. If the dimension of the face image to be trained is $M = N \times N$, then the dimension of the large matrix is $Y = j \times M$.

Add all the face dimensions in each column and average their values to get an "average face". Then all j face images are subtracted from the average face image, and a special matrix X with difference images can be obtained.

Through the theoretical elaboration and conclusions in Chapter Two, the matrix X is processed by covariance, namely $C = \frac{1}{m}XX^T$, and then its eigenvalues and its corresponding eigenvectors are obtained, and the eigenvectors obtained are the "eigenfaces" required by the experiment.

3.2 Eigenface extraction and face recognition

It can be seen from formula 10 that the larger the variance contribution rate is, the larger the corresponding top k eigenvalues, which means that the top k eigenfaces selected retain a large amount of main information. More, it also makes the subsequent experiments to restore the face image more and more clear. The recognition method used this time is the eigenface method. The face image is classified by comparing the extracted face features, and the closest target is the face image that the experiment is looking for. All face images to be detected first consider whether the size of the image is consistent, and then they will be mapped to the face space formed by the eigenfaces, that is, the coordinate system formed by the eigenfaces. Suppose the average face is $\overline{X}$, the image to be tested is $T_i$, a certain image is $t_i (i = 1, 2, \ldots, n)$, and the characteristic face is $\Phi$, then it can be expressed by formula 11.

$$T_k = \Phi_k^T (t_i - \overline{X})$$

Where k represents the corresponding k-th feature vector. Through this process, the face image to be tested can be mapped to the coordinate system of the feature face. Then, the distance between the face image to be measured and a face in the training set is judged. When the judged value is within a
certain threshold, the face image recognized by the experiment can be obtained. The determination formula is shown in formula 12.

$$d_i = \| T - t_i \|^2$$  \hspace{1cm} (12)

When the value of $d_i$ is less than a certain threshold, it can be considered that the input face image and a certain image are in the same category, and the matching is successful.

4. Human face two-dimensional code recognition simulation experiment

The simulation of this experiment was run in the environment of Matlab R2016b. In order to improve the success rate of the experiment, all the face images required for this experiment were downloaded from the ORL face database, and the principal component analysis method was used to train the face images. Save the trained data in the model.mat file, and you can load the data from this file during simulation. The realization of the two-dimensional code encoding and decoding mainly uses the ZXing open source library under the JAVA platform, which needs to be called during the experiment simulation, and finally the two-dimensional code is decoded and converted to the face.

4.1. Build PCA database

Before simulating this experiment, in order to minimize the influence of other factors such as light, makeup, background, etc. on the experimental results, 140 images in the ORL face database were selected as the experimental data set. These pictures were collected only at different times and under roughly the same conditions with other factors, and their sizes were all fixed, 92*112. The first 6 images in the ORL face database are shown in Figure 1.

Figure 1. 6 images in the ORL face database

Before testing the face image, we must first train the samples and then construct the PCA database to save. The resolution of any face image can be regarded as its feature points, or as the dimensions it is composed of. When the dimension is too high, the recognition rate will be low, so this step can make the face image trained as a matrix first, and obtain the eigenvalues and corresponding eigenvectors of its covariance matrix. Then arrange them in descending order. These feature vectors are the eigenface models, and then save them in the model.mat file.

4.2. Select face image

A total of 140 face images (10 per person) are selected in the loaded face library, and each photo is taken under the same lighting environment, and the shooting posture is roughly the same, and the image size is 112*92. An image 003.bmp in the face database is shown in Figure 2.

Figure 2. Image 003.bmp in the face database

4.3. Eigenvalue selection in dimensionality reduction

For the face image loaded above, its size 112*92 pixels can be regarded as a dimension of 1*10304, where 1 can be regarded as a picture, and the picture can be regarded as a matrix. In the data obtained after dimensionality reduction, the eigenvalues are arranged in descending order by size. In this simulation, to ensure the recognition success rate of the experiment, the first 90% of the eigenvalues are selected, that is, the contribution rate is greater than 0.9. In order to make the whole program look concise and convenient to call, this design encapsulates the PCA dimensionality reduction program.
4.4. QR code encoding
In this experiment code, the source code of ZXing is called, downloaded and packaged into a Jar file, and placed in the same directory as the calling function QrGen.m. Input the information that needs to be encoded during execution, specify the size of the generated two-dimensional code, and finally convert the information into Matlab image matrix data for output. In this process, it is only necessary to encode the reduced-dimensional face image data as a parameter with a two-dimensional code. Taking the first image in the face database as an example, the result of the encoding program used is shown in Figure 3.

4.5. Face recognition by QR code
Due to the large storage capacity of the two-dimensional code and the small space occupied, the two-dimensional code has a very good advantage in recognizing human faces due to the characteristics of being able to quickly crack it. The two-dimensional code decoding also calls the zxing open source library, and then edits the decoding process into the QrDen.m function. Its main function is to decode the two-dimensional code image, and the decoded character string or information is converted into an image format for convenient calling. After decoding, the reconstructed image of the face that is converted into the information is shown in Figure 4.

It can be seen from the experimental results that face images generally have the characteristics of large data dimensions, and the experiment can obtain effective information of the face by performing PCA dimensionality reduction, and perform two-dimensional code encoding and decoding. The ZXing two-dimensional code open source library called by the experiment has high experimental efficiency, which is beneficial to improve the operating efficiency of face two-dimensional code recognition and facilitate the machine to complete the simulation.

5. Summary
This article mainly introduces the feature extraction method, classification and recognition method of face QR code recognition, dimensionality reduction of PCA algorithm and its related principles. Analyze the QR code process after introducing the entire process of QR code in detail. The test is carried out in the simulation environment of Matlab, and the experimental principle and steps are given. After choosing different methods to try, the data selected in this experiment has higher experimental efficiency and better recognition effect. This experiment only uses a simple classification algorithm to recognize the face of the two-dimensional code, and there are many shortcomings, which can continue to be optimized and improved in the follow-up work.

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