Based on Rapid Fingerprint Identification Application in Railway Station Research

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Abstract. Principal component analysis (PCA) is a common feature selection algorithm, the classical PCA method is to calculate the correlation between the various features, but the correlation cannot evaluate the nonlinear relationship between variables, then present 2DPCA and Kernel 2DPCA. The method proposed in this paper is aimed at the situation where the passenger traffic is large and the passenger fingerprint information gathering is affected by the external factors. Two dimensions of two-dimensional nuclear principal component analysis (K2DPCA+2DPCA) can effectively solve non-linear separable fingerprint identification problems. At the same time, it can reduce the computational complexity of the template and reduce the storage space.

Introduction

The matching of fingerprint characteristics is a very important link in the fingerprint identification system, including the algorithm based on the graph image, the algorithm based on the ridge structure, and the algorithm based on feature point matching. At present, most automatic fingerprint identification systems (AFIS) are based on feature point matching. PCA is a classical linear feature point extraction method. When processing 2D images, the image matrix is transformed into one dimension row or column vector. But the dimension of one-dimensional vector space is very high, which leads to the calculation of the eigenvector of the high dimensional covariance matrix is quite time-consuming.

The principle of 2DPCA proposed in this paper is essentially consistent with PCA, but 2DPCA can directly process 2D images without the need for transformation vectors. In the process of image feature extraction, PCA and 2DPCA need to process a covariance matrix to obtain the projection matrix. These differences lead to very different covariance matrices that they have to deal with. For a \( m \times n \) image, PCA has to deal with a \( Mn \) order covariance matrix, while 2DPCA has to deal with a \( m \) (or \( n \)) order image covariance matrix. In practical problems, the covariance matrices of PCA and 2DPCA are estimated by their corresponding sample covariance matrices.

Theory and Algorithm

The basic idea of this method: first remove the correlation in the image line direction by using the standard K2DPCA method; then in the K2DPCA space in the column direction of the image by using the 2DPCA method to further remove the correlation image.

2DPCA

Let \( Z \in R^{m \times d} \) be a projection matrix orthogonal to each other, \( m \geq d \). By projecting the fingerprint \( A_i \) onto the \( Z \), the \( d \times n \) matrix \( T_i = Z^TA_i \) obtained and called \( T_i \) is \( A_i \) that the 2DPCA projection characteristic matrix. In order to obtain the optimal projection matrix \( Z_{opt} \), the objective function of 2DPCA is:

\[
J(Z) = \max_Z \{E[(Y - EY)(Y - EY)^T]\}
\]
In the above formula: \( t\{\} \) represents the trace of matrix. Order

\[
G = E[(A - EA)(A - EA)^T]
\]

Then \( G \) can be obtained by the above formula,

\[
G = \frac{1}{M} \sum_{i=1}^{M} (A_i - \bar{A})(A_i - \bar{A})^T
\]

Above formula: the average image of \( \bar{A} \) is \( A_i \in \mathbb{R}^{m \times n} (i = 1, 2, ..., M) \). Therefore

\[
J(Z) = \max_Z (Z^TGZ)
\]

In this way, \( Z_{opt} = (z_1, z_2, ..., z_d) \) can be obtained by solving the eigenvectors corresponding to the largest \( d \) eigenvalues of the global divergence matrix \( G \).

**K2DPCA**

KPCA is a non-linear feature extraction method for linear PCA [1]. The basic idea is to map the raw input space data to a high-dimensional or even infinite dimensional feature space \( F \) by a nonlinear mapping \( \Phi: \mathbb{R}^n \rightarrow F \), and then perform the PCA algorithm in the feature space \( F \).

At the same time, K2DPCA has a greater advantage in extracting nonlinear features of data. The similarity between K2DPCA and KPCA is that it is not necessary to directly know the nonlinear mapping function to complete the nonlinear mapping. The difference between K2DPCA and KPCA is that K2DPCA maps each column of the image matrix to the feature space \( F \) (e.g. nonlinear mapping \( \Phi: \mathbb{R}^n \rightarrow F \)), and then performs PCA analysis in this feature space. Because the dimension of \( F \) space is very high, it is impossible to perform the usual operations. Therefore, in order to be able to implement PCA in \( F \) space, the implicit computation of inner product kernel function can be used. The input data \( A_i \) and \( A_j \) are computed by function \( K \) are mapped into inner product in space \( F \) [2]. The expression is as follows:

\[
K(A_i, A_j) = \Phi(A_i) \cdot \Phi(A_j)
\]

In the above formula, \( \cdot \) expressed the inner product of space \( F \). Assume that all minutiae of a fingerprint are centralized, \( \Phi(A_i) \) expressed in the \( i \) space mapping amplitude mapping image, \( \Phi(A_j) \) expressed column \( j \) center vector of the amplitude mapping image \( i \). Then the covariance matrix \( C^\Phi \) of space \( F \) can be obtained:

\[
C^\Phi = \frac{1}{M} \sum_{i=1}^{M} \Phi(A_i)^T \Phi(A_i)
\]

In the above formula, \( \Phi(A_i) = [\Phi(A_i^1), \Phi(A_i^2), ..., \Phi(A_i^n)] \). \( M \) expressed the number of columns. It is very difficult to calculate the eigenvalue \( \lambda_i \) of the matrix directly, and the eigenvector \( v_i \) must be satisfied:

\[
\lambda_i v_i = C^\Phi v_i
\]

By using the following theorem, we can use KPCA to implement K2DPCA algorithm, so as to avoid the difficulty of direct calculation [3].

**Theorem:** assuming that each column vector acts as a computational entity, the K2DPCA algorithm is implemented by executing the KPCA algorithm on each column of the training image matrix. In order to extract each column vector of principal components, the need to project each \( \Phi(A_i) \) to \( x_k \) feature vector of space \( F \) and its projection expressions are as follows:

\[
(x_k \Phi(A_i)) = \sum_{p=1}^{M} \sum_{q=1}^{n} a_{pq} \Phi(A_p^q)^T \Phi(A_i^q)
\]

In the above formula, \( (l = M \times n - d + 1, ..., M \times n) \). By the above formula can get the projection \( Y_i \) from the \( i \) amplitude mapping image \( \Phi(A_i) \):
\( Y_i = \left( x_k \Phi(A_i) \right) = \alpha^T (\varphi^\Phi)^T \Phi(A_i) \) \hspace{1cm} (9)

In the above formula: \( \alpha = (\alpha_{M \times n - d + 1}, \alpha_{M \times n - d + 2}, \ldots, \alpha_{M \times n}) \) and the factor
\[ \varphi^\Phi = \begin{bmatrix} \Phi(A_1^1), \Phi(A_1^2), \ldots, \Phi(A_1^n) \\ \ldots, \ldots, \ldots, \ldots, \ldots, \ldots, \Phi(A_M^1), \Phi(A_M^2), \ldots, \Phi(A_M^n) \end{bmatrix} \]

The projection matrix of each image is obtained by projecting the column vectors of all training images and test images onto the first \( d \) feature space of the feature space, and the size is \( d \times n \) [4].

**K2DPCA+2DPCA**

K2DPCA can effectively overcome the shortcomings of 2DPCA algorithm in nonlinear feature extraction of the image, and its effect is better than that of 2DPCA and KPCA algorithm [5], but it needs more coefficients for image representation, which leads to reduce the speed of recognition, and require a lot of storage space.

In order to overcome the weakness of above K2DPCA, a new method is proposed. The basic idea of this method is as follows: firstly, the K2DPCA transform is performed in the direction, and then the 2DPCA transform is performed in the column direction of the K2DPCA subspace. For a given image matrix \( A \), after the K2DPCA transform, we can get its characteristic matrix \( Y \). Then transpose the \( Y^T \) and transpose the matrix into 2DPCA transform to determine the transformation matrix \( V \). Finally, the \( Y^T \) is projected \( V \), thus the \( C^T = Y^T V \) is obtained, and the feature matrix is \( C = V^T Y \).

Process as follows.

![K2DPCA+2DPCA transformation process.](image1)

**Experiment and Result Analysis**

Firstly, a fingerprint image database is constructed, which consists of 10 different finger detail points. Each sample is composed of 8 images collected at different times, and the light difference of these images is nonlinear. These images are all images with 256 gray pixels and normalized to 32×37. The proposed K2DPCA+2DPCA method and the K2DPCA algorithm are compared in a series of different dimension eigenvectors, and the results are shown below.

![K2DPCA+2DPCA comparison of algorithms.](image2)

**Summary**

To sum up, it can be seen that the difference between K2DPCA+2DPCA and K2DPCA algorithm is that the latter is only analyzed in vertical direction, and the method proposed in this paper is used to analyze the projection in horizontal and vertical directions simultaneously. The main advantage is
that the fingerprint minutiae can be described by a small amount of coefficients. The projection processing can achieve the purpose of dimensionality reduction, and the computational efficiency is higher than that of the K2DPCA algorithm, which greatly reduces the loss of system calculation cost, and has higher recognition rate. Experimental results show that compared with K2DPCA algorithm, the proposed algorithm has faster recognition speed and higher recognition rate, and also verifies the effectiveness of the algorithm in fingerprint minutiae recognition.

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