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HUMAN FACE RECOGNITION METHOD BASED ON MULTI-LINEAR FUNCTIONS

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ABSTRACT

This paper undertakes the researches of face recognition problems in the conditions of different illuminations and viewing angles. To solve the problem of decreased human face recognition, this paper proposes a tensor-based multi-linear human face recognition method. First, we adopt the form of tensor to represent the image in human face database, and then, depending on different training individuals, we divide the original human face space into some subspaces, and obtain reflection transformation equations for their corresponding subspaces. In the recognition process, we can transform the reflection of the measured face images in different sub-spaces. Meanwhile, we have to calculate the amount of lost information before and after transformation. Thus, we have the human faces classified and identified. The main advantages of this method are reflected as follow: 1) Maintain the spatial relationships between the face images in the adjacent row vector and column vector by using tensor. 2) We can realize human faces recognition by adopting a simple linear transformation, with which we can have this algorithm been with a high recognition rate and a better computational complexity.

Keywords: *Human Face, Tensor, Nonlinear*

1 INTRODUCTION

Although the human face recognition technology has been considerably improved in recent years, there are still many factors in restricting its practical applications. For example, the traditional human face recognition techniques based on PCA theory will stretch a human face image to a one-dimensional vector. In addition, on the basis of XOR value decomposition, the technique will find a new reflection space to make the spatial distribution of each single face image discrete in the spindle direction to achieve the purpose of identifying human faces. However, XOR value decomposition of this method should be conducted on $N_1 \times N_2 \times N_1 \times N_2$ (N_1 and N_2 refer separately the image length and the width), in this condition, the computation is of a huge amount which will lead to a low computational efficiency [1]. For other vector space based methods, such as LDA, LLD, are susceptible to the influences of the factors like illuminations, viewing angles, expressions, and so on, to make the recognition accuracy rate decreased.

From a more intuitive point of view, an image is represented in form of a matrix in the collection process, so two-dimensional space-related information is easy to be lost in traditional vector algorithms, its, which will easily lead to a decreased identification for following algorithms. In order to diminish limitation for vector methods, the scholars have put forward a mathematical model which can represent the face images in a tensor form. In the mathematical sense, one-dimensional vector can be regarded as a one-order tensor, and the matrix a second-order tensor. If we take time series and other information, such as video information, into consideration, we can just regard the 3D video information as a three-order tensor, so as to other higher order tensors.

If a human face image is presented in the form of a matrix (a two-order tensor), we can take advantages of the space correlation of the vectors between adjacent columns or rows, and such correlation can be maintained after the reflection transformation. The favorable characteristics have more advantages, especially in the case which is of fewer training samples [2].

In addition, the previous human face recognition methods focused more on linear methods (PCA, LDA) or kernel-based nonlinear methods [3]. The major shortcoming of the former ones is that such models are simple, so that we cannot accurately describe the information such as illuminations, viewing angles, and so on. While the shortcoming of the latter models is that they are too complicated, so that the computational efficiency is very low.

With the application of this tensor method based on flow theory, the multi-linear function [3] method

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gradually receives attention and development in the field of human face recognition. For the tensor-based methods, different characteristics of a human face can be shown as a combination of different weights and tensors. In this condition, we can apply such methods for human face recognition to adapt to more scene changes.

In this paper, we have proposed a human face recognition method with tensor based on individual-specific characteristics model, through which we can fully describe information on human face images such as illuminations, viewing angles, and so on. For individuals in a training sample, we can extract their corresponding feature vectors as the basis of the coordinate system for the said sample. In different training samples, we can divide the entire corresponding feature space of the human face into several limited subspaces. Though the reflection transformation in the entire feature space, due to its nonlinear characteristics, will lead to an information loss, the reflection transformation will maximize keeping the original information each from being lost in each sub-space because of its local linear features. Based on this principle, we can ensure to make full use of the spatial information contained in tensor in human face recognition process.

2 THE EXPRESSION OF HUMAN FACE TENSOR

For a human face database, assuming that there are various illumination conditions and viewing angles contained in face images, the face images in the database can be expressed in the tensor function shown as follow:

$$T(i_p, i_l, i_v) = I_{P_{i_p}, L_{i_l}, V_{i_v}} \quad (1)$$

where $I_{P_{i_p}, L_{i_l}, V_{i_v}}$ refers to the human face image obtained from the sample numbered i_p in the database with illumination condition numbered i_l and viewing angle numbered i_v, while T refers to a four-order tensor, which meets the requirement as follow:

$T \in R^{N_p \times N_l \times N_v \times N_x}$, where N_p refers to the number of various individuals, N_l and N_v refers to separately the numbers of different illuminations and viewing angles, while N_x refers to the size of the image vectors in vector form.

For a multi-linear PCA calculation which is carried out in a tensor space, we adopt the environment of a high-dimensional SVD (HOSVD). This method has been discussed in references [2] and [4]. HOSVD will generate four subspaces for the tensor T, among which each subspace is corresponding to different variances of modes. The transformation can be expressed as the following function:

$$T = S \times_1 U^P \times_2 U^L \times_3 U^V \times_4 U^X \quad (2)$$

Where $\times_k$ refers to a point multiplier for the model numbered k. The column vectors in matrix U^P, U^L, U^V and U^X represent separately the corresponding subspaces of the individuals, brightness, viewing angle and image pixels. The column vectors in matrix U^X represent the eigenface of the corresponding face image. According to the principle of PCA similarity theory, in matrix U^P, U^L ,and U^V, the former $N'_p (\le N_p)$, $N'_l (\le N_l)$ and $N'_v (\le N_v)$ featured vectors, as well as the main feature vectors, and their corresponding values, represent separately the elements of individuals, illumination and viewing angles in their feature subspaces.

3 THE REFLECTION METHOD BASED ON MULTI-LINEAR SUBSPACE

If we use multi-linear characteristic model to decompose and identify the face tensor, according to function 2, we can obtain the function as follow:

$$A = S \times_4 U^X \quad (3)$$

where A is a intermediate tensor, which can be extended as follow:

$$A_p = \begin{bmatrix} I_{P_1^e L_1^e V_1^e} & \cdots & I_{P_1^e L_{Nl}^e V_{Nv}^e} \\ I_{P_2^e L_1^e V_1^e} & \cdots & \cdots \\ \cdots & \cdots & \cdots \\ I_{P_{Np}^e L_1^e V_1^e} & \cdots & I_{P_{Np}^e L_{Nl}^e V_{Nv}^e} \end{bmatrix} \quad (4)$$

where $I_{P_i^e L_j^e V_k^e}$ refers to a specific multi-linear featured model.

Such multi-linear featured models are applied to form the reflection coordinate base for different modes. The coefficients corresponding to the reflection vectors for the training data can be obtained with the matrixes U^P, U^L, and U^V. However, if we undertake the reflection transformation in accordance with the Function 4, we can find the computational complexity for the next test image will be $O(N_p \times N_l \times N_v)$.

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In order to reduce the computational complexity of the reflection transformation, we change the idea of the previous algorithms, which make the factors of illuminations, viewing angles as the reflections, into the idea of regarding the same training individual as the characteristic mode to get a new reflection base. In this condition, according to a method which is similar to Function 3, we propose an assumption as follow:

$$B = S \times_1 U^P \quad (5)$$

Similarly, we can get:

$$B_p = \begin{bmatrix} I^e_{P_1 L_1^e V_1^e} & \cdots & I^e_{P_1 L_{Nl}^e V_{Nv}^e} \\ I^e_{P_2 L_1^e V_1^e} & \cdots & \cdots \\ \cdots & \cdots & \cdots \\ I^e_{P_{Np} L_1^e V_1^e} & \cdots & I^e_{P_{Np} L_{Nl}^e V_{Nv}^e} \end{bmatrix} \quad (6)$$

Where $I^e_{P_{ip} L_{il}^e V_{iv}^e}$ refers to the corresponding featured image of the characteristic brightness numbered i_l and the featured viewing angles numbered i_v of the training sample (individual) numbered i.

If we define:

$$B_i = \begin{bmatrix} I^e_{P_i L_1^e V_1^e} \\ I^e_{P_i L_2^e V_1^e} \\ \cdots \\ I^e_{P_i L_{Nl}^e V_{Nv}^e} \end{bmatrix} \quad (7)$$

where the value of the parameter i is $1,\cdots,N_p$, which refers to point each training object (individual). Thus for a test sample I_T, the reflection of which on base B_k has a physical meaning: In the subspace generated by training individual k, the test sample represents the combination form of the vector representing brightness and the one representing prospect.

Because the samples used to constitute B_k are actually only a small number of samples for a certain individual, we can find that B_k is in corresponding to a comparative smaller subspace in the overall featured space. Therefore, the reflection transformation in B_k can be regarded as an approximated linear transformation for better maintaining the original image information. If the test sample I_T is chosen from individual k, then the reflection of I_T on B_k, comparing with the ones on other subspaces, can maintain maximum original information.

According to this principle, by applying the smallest reconstruction error, we can infer the amount of lost information before and after reflection, and thus to set the foundation of human face recognition method. The specific procedures are shown as follow:

Input the human face images for testing;

Calculate the reflected image: $I'_T = I_T \times U^X$;

Calculate the equations $c_i = I'_T \times B_i$, $I_T^r = c_i \times B_i^T$, and $e_i = \| I'_T - I_T^r \|$ separately for each individual with the number $i = 1,\cdots,N_p$;

Selecting e_k, which is the minimum value, the corresponding individual of parameter k is of the same category of I_T.

In the third step, B_i^T refers to the generalized inverse transformation for the matrix. Here we adopt Euclidean distance in presenting the results.

In above steps, we only have to conduct N_p matrix multiplication computations and N_p sub-Euclidean distance calculations. In this condition, we can find the computational complexity of the proposed algorithm is $O(N_p)$ which is faster than the methods mentioned above with two orders in this paper.

4 EXPERIMENTAL SETUP AND RESULTS

In order to verify the effectiveness of the proposed method, we conducted a comparison test on ORL human face database and Yale human face database. In ORL database, there are totally 40 different individuals, among which each individual contains samples of different camera angles and different facial expressions. The human face rotation angle ranges between positive and negative 17 degrees. Fig 1 shows the samples in a testing individual.

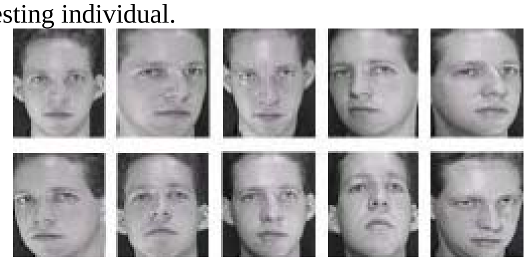

Fig. 1 Samples In ORL Database

In Yale database, there are overall 15 individuals, in which there are various human faces samples under different illumination and with expressions. Fig 2 shows a demonstration of the samples in Yale database.

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Fig 2. Samples In Yale Database

Before the test, firstly we have to cut the original face image to the ones with a size of 64×64 to make only human face shown in this region.

In order to compare test results, we have adopted the PCA algorithm based on vectors, facial classification and recognition algorithm and the method proposed in this paper based on High Oriented Singular Value Decomposition (HOSVD). In Fig 3, we have compared the recognition accuracy of such three methods. According to the Fig, the recognition effect of the three methods on Yale database is better than that on ORL database shows that the sensitivity of image brightness is lower than that of viewing angles. According to the Fig, we can find that the recognition accuracy of this method is higher than that of the other two methods.

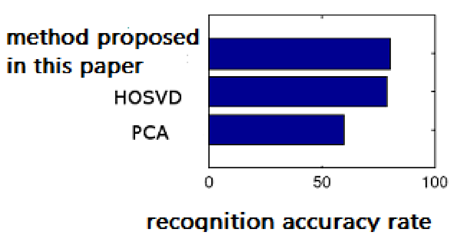

Fig 3. Samples In ORL Database

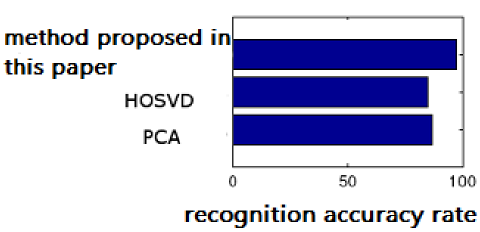

Fig 4. Comparison Of Recognition Accuracy Rate

TABLE I : Complexity Of Computing Time (Second)

	ORL	YALE
Method Proposed in This Paper	1.0	0.3
HOSVD	22	1.1
PCA	1.7	0.7

In Table I, we list the time required for the two databases with three different ways in the test. The test environment we have adopted is based on the computers with configuration of: Intel 1.6G, 64-bit CPU, Windows 7. with which, the average computation time for recognizing faces in the ORL database with the proposed method was 1.0 second, the time in YALE database was 0.3 second. In general, the average computational times taken by these two methods are significantly better than the times taken by other two methods.

5 CONCLUSIONS

In this paper, we propose a face recognition method based on tensor. Different from the previous vector-based algorithms, the one proposed in this paper make full use of the advantages of the tensor in maintaining correlation between each row vector and column for the image, which has significantly improved the recognition accuracy. In addition, with the application of the multi-linear functions, we can divide the original face image into a number of sub-spaces for different training individuals, and then reflect each subspace of the human face image to ensure a linear transform of the reflection in a local region, and keep maximum information before and after the reflection. The algorithm proposed in this paper is of the characteristics of high computational efficiency and high identification accuracy.

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