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Vein Recognition Based on (2D)2FPCA

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Abstract

The importance of biometric identification technology in the field of information security is increasingly prominent, in various of recognition technology, hand vein recognition technology attracts more and more researchers' attentions because of its high security and high recognition rate; The traditional template matching method based on vein skeletal morphology inevitably brings about problems such as long training time and too much space occupation of sample storage; the passage applies feature extraction method based on the subspace to the vein recognition on the basis of analysis of the principal component analysis method, which is called (2D)^{2}FPCA algorithm combining the traditional 2DPCA and 2DFLD technology; the new algorithm has many advantages including reduction of the preprocessing algorithm steps and small space occupation of characteristics vectors with high processing speed; Finally, simulation experiments with the new algorithm are carried out in 500 vein image database, which proves that the method not only has better recognition accuracy but also improves the recognition rate while reducing the storage space.

Keywords: *The hand vein, The principal component analysis method, Fisher linear transform ,The recognition rate , Feature matching*

1. Introduction

The traditional vein recognition focused more on recognition method based on template matching, which was easy to realize while needed a complex process to extract vein skeleton information for the aim of comparing it with the template library in great detail, along with the problem that low recognition rate in great time consuming when the database space had a large amount. To solve this problem, we could extract the subspace feature of the vein image to improve the system recognition rate as well as lowered storage space. There were many typical representation of linear feature and data extraction method, the two of which were called PCA & FLD were widely adopted in the field of pattern recognition. When we adopted the two methods to realize two-dimensional digital image processing, the problem of having high dimension vector space resulting time consuming and difficult to realize accurate estimation of covariance matrix when the number of samples were relatively small after a series of mathematical transformation of the image matrix into one-dimensional row or column vector.

In the view of the above situation, J. Yang [1] firstly put forward 2DPCA in 2004, then Li [2] and Xiong [3] put forward 2DFLD in 2005, the former was to construct the corresponding covariance matrix on an image, then used 2DPCA in the row direction, while the latter in the column direction. We could get the conclusion that both the 2DPCA [4] &2DFLD needed more coefficients to express the image information accurately while comparing with the traditional PCA. To solve this problem, the passage introduced one method which combined 2DPCA and 2DFLD Inspired by the literature [5] .The method could be divided into two parts, the first part which eliminated the correlation of the vein image in the row direction by 2DPCA method involved dealing vein recognition with $(2D)^2$FPCA, then eliminate correlation in the column direction of the processed image using 2DPCA,which had achieved good recognition effect on the behalf of reducing the storage space.

2. The Basic Concept of 2DPCA

Principal components analysis was a kind of compression technology based on optimal dimensionality with the minimum mean square error, the characteristic component of which was entirely unrelated,1DPCA was the method converting a digital image into a 1D array resulting a highly dimensional covariance matrix, while having to use singular solution to get the feature vector. In the view of this situation, 2DPCA realized the transform of image matrix directly to avoid the large dimension of the covariance matrix.

Assuming the existence of M training samples with C modes [6], while M_i stood for the amount of the ith sample and $A_j^{(i)}$ stood for the jth sample of the i category in the $m \times n$ matrix. $\overline{A}^{(i)}$ The mean of training samples in the i category, $\overline{A}$ stood for the overall mean of training samples.

Assuming the existence of a $m \times n$ random image matrix A, the $X \in R^{n \times d}$ within $n \geq d$ stood for standard orthogonal matrix in a column vector, projecting the image vector A onto the orthogonal matrix X to get a $m \times d$ matrix, which meant $Y = AX$. In the subspace, we could get the total scatter matrix of the sample projection with the orthogonal matrix, As shown in equation 1:

$$\begin{aligned} J(X) &= trace\{E[(Y - EY)(Y - EY)^T]\} \\ &= trace\{E[(Y - E(AX))(Y - E(AX))^T]\} \\ &= trace\{X^T E[(A - EA)^T (A - EA)]X\} \end{aligned} \tag{1}$$

Among them, for two matrices of arbitrary, equation 1 could conclude trace(AB)= trace(BA).

Defining the image covariance matrix as $n \times n$ nonnegative definite matrix $S_t = E[(A - EA)^T (A - EA)]$, assuming the existence of $m \times n$ matrix $A_k (k = 1, 2, \ldots, M)$ with a total of M images for training, S_t could be calculated by the following formula:

$$S_t = \frac{1}{M} \sum_{k=1}^{M} (A_k - \overline{A})^T (A_k - \overline{A}) \tag{2}$$

Therefore, the best projection X_{opt} of the projection matrix was made up by the largest characteristic value of the former d orthogonal eigenvectors $x_1, \ldots, x_d$ in which was $X = [x_1, \dots, x_d]$.

Assuming that $Y = AX$, and $X = [x_1, \dots, x_d]$,the matrix Y could be used to describe image A and realize the classification of the image database.

3. The Basic Concept of (2D)2FPCA

3.1. $(2D)^2$FPCA Algorithm

The method called 2DPCA could not only eliminate the image correlation in the row direction but also ultimately compress the information used for distinguishing in the row direction into the relatively little column matrix, but it ignored the relevance in the column matrix of the image, which meant compression was necessary for the same vertical direction resulting the phenomenon that the compression ratio of 2DPCA was more less than that of PCA, and at the same time the method of 2DPCA needed more coefficients in the description of the image bringing the disadvantage of a larger memory space and a less image classification speed when dealing with large database[7].

To solve this problem, the passage introduced one method which combined 2DPCA and 2DFLD,it firstly eliminated the correlation of the vein image in the row direction by 2DPCA method involved dealing vein recognition with (2D)2FPCA to get the characteristic matrix Y then dealing the feature matrix with transpose operation to get Y^T,then we could get matrix V after two-dimensional Fisher linear transformation, projecting it onto V, thus we could get the characteristic matrix $C = V^T Y$.This method could avoid the disadvantage of 2DPCA,the transform of the algorithm was as shown in Figure 1:

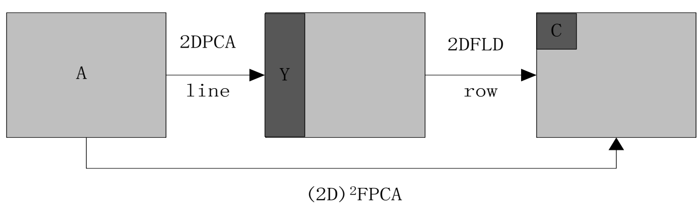

Figure 1. Transformation Process of $(2D)^2$FPCA

In the transformation process, the method called 2DPCA could not only eliminate the image correlation in the row direction but also ultimately compress the information used for distinguishing in the row direction into the relatively little column matrix using two-dimensional PCA transform $Y = AX$, then dealing the feature matrix with transpose operation to get Y^T,then we could get matrix V after two-dimensional Fisher linear transformation, projecting it onto V, thus we could get the characteristic matrix $C = V^T Y$,the distinguishing information of the whole image would be compressed in a corner of the image in the end.

3.2. The Transform of DFLD

Fisher linear transformation also was a common method of image compression [8], Fisher's criterion function was set to find a projection direction which could better gather the same class samples together, while the different sample were dispersed, we could get the characteristic matrix Y used as training image after 2DPCA transform in the row direction, then got the transposed matrix Y^T, Y^T could be used for constructing the image within-class scatter matrix H_w and the between class scatter matrix H_b,as shown in the following formula:

$$H_b = \frac{1}{M}\sum_{i=1}^{c} M_i(\overline{Y_i} - \overline{Y})(\overline{Y_i} - \overline{Y})^T \tag{3}$$

$$H_w = \frac{1}{M}\sum_{i=1}^{c}\sum_{j=1}^{M_i}(Y_j^{(i)} - \overline{Y}^{(i)})(Y_j^{(i)} - \overline{Y}^{(i)})^T \tag{4}$$

$$Y_j^{(i)} = A_j^{(i)}X\ ,\quad \overline{Y}_j^{(i)} = \overline{A_j}^{(i)}X\ ,\quad \overline{Y} = \overline{A}X\ .$$

Thus, the within class scatter matrix and the between class scatter matrix both were non-negative definite matrix [9], we could concluded from the research results of YANG that H_w was nonsingular after 2DPCA transformation. To find the optimal projection axis V which made the total scatter matrix maximum of the projection samples, the related Fisher criteria were given below:

$$J(V) = \frac{VH_bV^T}{VH_wV^T} \tag{5}$$

We could see that the solution of the formula could be concluded only if getting the feature vector of $H_w^{-1}H_b$, which covered the eigenvector of the q largest characteristic value of matrix $H_w^{-1}H_b$ [17]. In the end, we could get the characteristic matrix of every training image after projecting the untrained image onto, which demanded $V = (v_1, v_2, \ldots, v_q)$,after the operation of

$$C = V^TY = V^TAX\ . \tag{6}$$

To get the two-dimensional Fisher feature matrix of Y.

Because the value of p and q had been less than m and n, the dimension of the characteristic matrix would always be less than that of matrix of A and Y used in the transform of 2DPCA [10].

4. Feature Matching

The algorithm steps of $(\mathrm{2D})^2$ FPCA were as follows [11]:

4.1. The Training Phase:

Input：Image set $A_i^j \mid i = 1\ldots c,\ j = 1\ldots M_i$

Output：set $F = \{C_i^j \mid i = 1\ldots c,\ j = 1\ldots M_i\}$

The training phase algorithm：

(a) The first space conversion： $phase1: IR^{m\times n} \xrightarrow{2DPCA} F_1^{m\times d};$

Firstly, constructing the total scatter matrix S_t in space $IR^{m\times n}$

Secondly, calculating the standard characteristic vectors of the total scatter matrix S_t, set the former d positive characteristic values as $x_1,\dots,x_d$.

Finally, using 2DPCA algorithm to get the characteristic matrix $x_1,\dots,x_d$ which could convert the input image onto the $m\times d$ dimensional $F_1^{m\times d}$

(b) The second space conversion: $F_1^{m\times d} \xrightarrow{\text{2D-FLD}} F^{q\times d}$;

Firstly, the within class scatter matrix H_w and the between class scatter matrix H_b in space $F_1^{m\times d}$

Secondly, getting the feature vector besides $H_w^{-1}H_b$

Then, choosing the feature vectors $v_1, v_2, \dots, v_q$ against the former q matrix $H_w^{-1}H_b$,set $V=(v_1, v_2, \dots, v_q)$

The final output of the conversion results were as follows : $F=\{C_i^j = V^T AX \mid i=1\dots c, j=1\dots M_i\}$

Finally the training process of $(2\mathrm{D})^2$ FPCA ended.

4. 2. The Recognition Stage:

The input testing image was $I(m\times n)$, The optimal projection axis were respectively X and V ,while the output was the sample of image I .

The recognition phase algorithm:

(a)Getting the characteristic matrix $I^{|}$ of the input image I after the optimal projection axis X ,and $I^{|} = V^T IX$

(b)Resulting F_r^s making $\left\| I^{|} - F_r^s \right\|_2 = \arg\min(\left\| I^{|} - F_i^j \right\|_2, i=1\dots c, j=1\dots M_i)$,the symbol of $\|\cdot\|$ stood for euclidean distance

(c)Dividing the testing image I into r kinds, then the recognition algorithm is over.

5. Experimental Results

The experiment in the passage adopted the hand veins of 50 as sample, each of which was adopted 10 samples in different period that consists of 500 numbers vein image of database [12], but there existed tiny differences in light and location because of the time, so the database reflected the real vein image against the condition of differences in light and location well. After the referred ROI extraction algorithm and the pretreatment process, we could get an effective area whose size was 128×128, then dealt the sample to realize normalized size and gray level, feature extraction and recognition through $(2\mathrm{D})^2$ FPCA [13].We usually extracted a random sample of five images as training samples, the other five ones would be used for recognition, figure 2 was the part of venous sample hand vein image database in the same person.

Figure 2. Samples of the Same Person in the Database of Palm-dorsal Vein Image

This experiment was mainly about using two experimental verification algorithm to prove the recognition performance of $(2D)^2$ FPCA [14],the one of which was changing the number of feature vectors of $(2D)^2$ FPCA algorithm to compare the algorithm recognition rate; the other one was through changing the number of training samples to verify the fact that the algorithm change was suitable for small samples, which improved the recognition rate of the traditional algorithms and proved the $(2D)^2$ FPCA algorithm was suitable for hand vein recognition as well.

Table 1. The Highest Recognition Rate of Changed Overall Scattering Matrix

Algorithm	The number of feature vector for S_t	5	7	9	11	13
2D-PCA	The highest recognition rate (%)	94.29.	93.33	93.33	93.33	93.33
	The characteristic matrix size	128×5	128×7	128×9	128×11	128×13
Proposed method	The highest recognition rate (%)	84.30	95.71	94.29	94.29	94.29
	The characteristic matrix size	3×5	5×7	7×9	9×11	7×13

The chart showed the recognition after changing the number of characteristic vectors when the number of training sample was 2 of 2DPCA algorithm and $(2D)^2$ FPCA algorithm ,we could conclude from the chart that the recognition gradually stabilized with the characteristic vectors change of S_t ,when d = 5, 7, 9, 11 and 13,we could see that the recognition of $(2D)^2$ FPCA algorithm could reach 95.71% when $d = 7$, $q = 5$,and the size of characteristic vector was 7×9 while the recognition time was 1.43s[15], But when adopting 2DPCA algorithm, we could see that the recognition of 2DPCA algorithm could reach 94.29% when $d = 5$,and the size of characteristic vector was 128×3 ,so we could concluded that $(2D)^2$ FPCA was superior than the traditional 2DPCA in recognition and the space of the data.

Table 2. The Highest Recognition Rate of the Algorithm of 2DPCA and 2D)^{2}FPCA

The number of training samples	1	2	3	4	5
2D-PCA	-	96.25% $d = 40$	95.71% $d = 30$	95% $d = 20$	97% $d = 10$
$(2D)^2$ FPCA	-	95.71% $d = 40$, $q = 40$	97.1% $d = 30$, $q = 4$	98% $d = 20$, $q = 6$	98% $d = 10$, $q = 6$

In order to verify the new algorithm was also applicable to small samples, we would compare the recognition of $(2D)^2$ FPCA algorithm and 2DPCA algorithm through changing the number of training samples, the result was as shown in chart2.We could see that the highest recognition rate of $(2D)^2$ FPCA algorithm could reach 98% while the highest recognition rate of 2DPCA algorithm just reached 97%.When the recognition rate of $(2D)^2$ FPCA algorithm and 2DPCA algorithm respectively reached the highest, the sample numbers of $(2D)^2$ FPCA algorithm was 4 while the sample numbers of 2DPCA algorithm was 5,during which time the characteristic vector from projection of $(2D)^2$ FPCA was less than that of 2DPCA algorithm. Besides, The size of total scatter matrix was $\mathrm{n} \times \mathrm{n}$ when adopting $(2D)^2$ FPCA , while the size of the within-class and between-class scatter matrix were $\mathrm{m} \times \mathrm{m}$,which resulted more conducive to improve computing performance. It proved that $(2D)^2$ FPCA was also suitable for the small sample problem because that both H_b and H_w were small. The $(2D)^2$ FPCA algorithm could compress image data in high dimensional space again to obtain fewer coefficients and improve the system recognition rate when comparing with 2DPCA algorithm. At the same time, the algorithm in the passage improved the recognition rate while greatly reduced the recognition time when comparing with the referred method based on template matching in the last chapter.

Acknowledgements

The passage put forward the idea that adopting the subspace feature extraction method for hand vein recognition[16], compared the $(2D)^2$ FPCA algorithm which combined 2DFLD and 2DPCA with traditional 2DPCA, 2DFLD algorithm, the algorithm not only realized using fewer coefficients to describe the effective area of hand vein but also carried out experiments to verify the fact in the hand vein image database, the result concluded that the algorithm not only reduced the recognition speed but also got higher recognition rate, which improved subspace based feature extraction method was more suitable for hand vein recognition.

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