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Face Recognition Based on Singular Value and Feature-matrix

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***Abstract*—The face recognition algorithms based on singular value decomposition (SVD) have low recognition accuracy due to the common essential defect which singular value vector of arbitrary two face images have the different basis spaces in genera1. According to this, a weighted adaptive algorithm based on some important partial features is proposed. It normalizes different faces and then locates the features of eyes, nose and mouth with horizontal and vertical projections. Subsequently, local features of the key parts of face are extracted and weighted respectively by singular value to get the feature-matrix. Dynamic method of how to choose the weights of local features and formula of how to obtain the feature-matrix is given. Finally, the developed support vector machine is utilized to recognize faces. Experiments show that the proposed algorithm can not only calculate efficiently and work easily, but also deal with low recognition rate issues in SVD, which shows a good potential of application.**

Key words—face recognition; feature extraction; singular value decomposion; feature-matrix

I. Introduction

Face recognition has been an active and popular research topic in computer vision and pattern recognition community over the past few decades due to its wide and potential applications, such as surveillance, human– machine interaction, access control and so on [1]. Generally, the performance of a face recognition system depends on many factors, and face representation is unquestionably one of the most important components and plays a crucial role in a face recognition system. Existing face representation approaches can be mainly divided into two categories: geometric-based and appearance-based [2]. As geometric-based methods are very sensitive to illumination and expression variants, appearance-based methods have been more popular for face representation and recognition.

Appearance-based face representation methods directly represent an m×n face image into a mn×1 vector and then apply some statistical learning tools to extract features for subsequent recognition. Two representative statistical learning algorithms include principal component analysis (PCA) and linear discriminant analysis (LDA) [3-6]. While these two methods have achieved reasonable performance in face recognition, they directly manipulate each face sample on the gray level values of the image pixels. Hence, they are also sensitive to large illumination variation. Many improved face representation methods have been proposed recently to mitigate this problem and the most representative one is the singular value decomposition (SVD) based recognition method which uses the singular values as the feature vectors. The effectiveness of SVD has been tested by Z. Hong and YQ Cheng respectively.

singular values (SVs) based method due to the SVs contain little useful information for face recognition and most important information is encoded in the two orthogonal matrices of the Singular Value Decomposition (SVD) [7-9].

In this paper, a new method is proposed for face recognition. This method consists of three parts. Firstly, normalization, edge detection and projection are done to obtain facial matrix; secondly, the face image features are extracted by using matrix calculation; finally, weighing image matching are executed to verified the feasibility of this method.

II. Normalization Process of Face Image

The method is done to normalize different face images into the same size due to different human may have different wide or long faces. The singular value amount of one face image to be recognized should be in accordance with the one in the feature database, which makes it easier for feature matching operations.

Suppose that the standard face images in the database are about 100×100 while the one recognized is $L\times W$, thus L and W should be shortened or magnified with the same proportional scales, e.g., if $W<L$ the image is zoomed $100/L$, else if $W>L$ zoomed $100/W$. It is unnecessary to execute gray normalization, illumination compensation, dimension depression and wave filter for the images in the database owing to these images are standard face images and they are immunity from the varieties of illuminate intensity.

III. Feature Location of Face Image

It is necessary to locate the facial features or block the face image before extracting the singular values in order to simplify the calculation and improve the recognition precisions.

A. *Feature location based on gray projection*

Facial components with little tilting degree face have plenty of edge information in vertical direction. And the edge information are traditionally obtained by using all kinds of edge detection operators. The locations of the facial components could be identified clearly by using image binary of adaptive gray threshold on the basis of the edge information.

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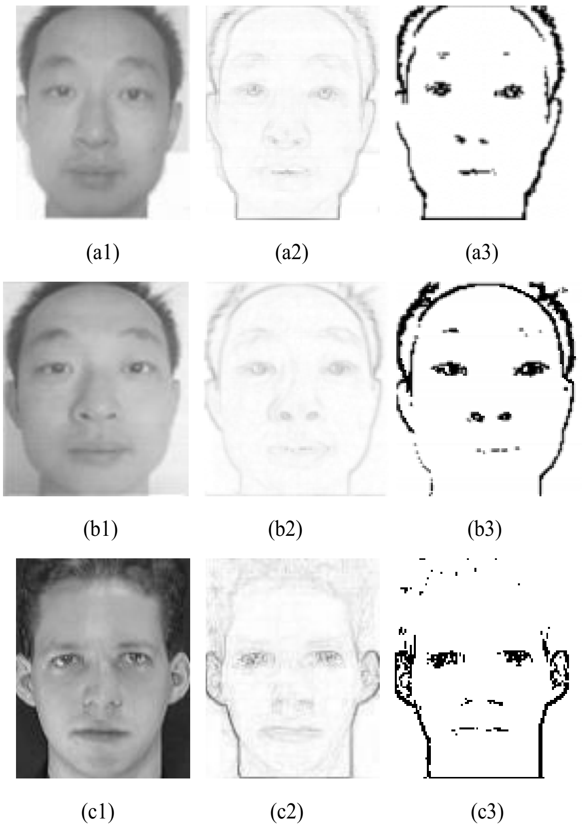

Figure 1. Edge extraction and binarization of the face images

Some edge information, e.g., forehead and chin are wiped off while eyes, nose and mouth are reserved in order to facilitate the horizontal projection processing of the binary images.

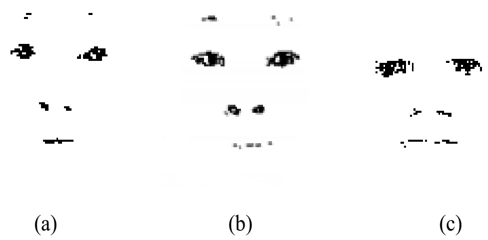

Figure 2. Facial components without profile

The vertical locations (y1, y2, y3) of eyes, nose and mouth could be obtained from the gray peaks of the horizontal projection of the face image without facial profile. Some human eyebrow features are not obviously especially for the race without yellow skin, whose eyebrow information are very less after their face image is edged and binarized. So the eyebrow information are ignored according to the eyebrows are neighbor to eyes. The horizontal projection of Fig.2 (a) is as shown in Fig.3.

The central locations of eyes, nose and mouth in vertical direction are y1=45, y2=70, y3=87 separately according to the locations of wave troughs in the image. The horizontal locations of left eye, right eye, nose and mouth are x1=24, x2=63, x3=42, x4=42 separately according to the vertical projection of Fig.2 (a), shown as Fig.4.

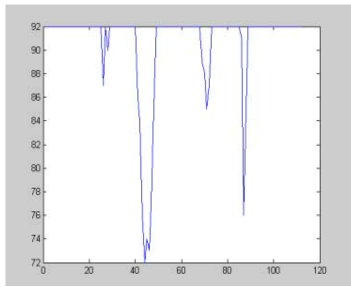

Figure 3. Horizontal projection of Figure.2(a)

As mentioned above, the central locations of left eye, right eye, nose and mouth of the face image shown in Fig.1(a1) are respectively Leye(24, 45), Reye(63, 45), Nose(42, 70), Mouth(42, 87).

With the same method, the central locations of left eyes, right eyes, noses and mouths of the face images shown in Fig.1(b1) and Fig.1(c1) could be ascertained as Leye(27, 46), Reye(67, 46), Nose(47, 72), Mouth(47, 88); Leye(26, 52), Reye(65, 52), Nose(46, 4), Mouth(46, 87) respectively.

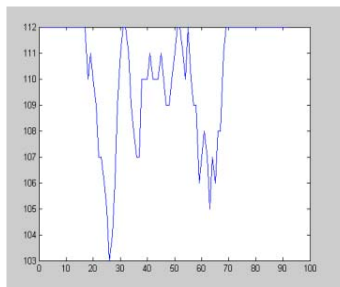

Figure 4. Vertical projection of Figure.2(a)

B. Feature sampling based on windows

Aimed at the two issues mentioned in the begin of this part, based on the theories above, and combined with the actual engineering test, the spatial sampling criterion for recognition of structural objects is put forward: there must be a maximal rotary step $m°$ ($m \ge n$) for any 3D object whose least recognition structural size ascertained in advance, the $M = 360/m$ images $X_1, X_2, \cdots, X_M$ obtained from $0°$ to $360°$ with the step $m°$ include the completely structural information for recognition. $m°$ is restrained by the least structural size l_{Min} and the inherent resolution of the imaging system that includes the sensitivity for different grays and the spatial resolution for different sizes.

Suppose that the image width is about *W* while its height *H*, the process of feature extracting for face image could be seen as one moving sampling process with the same distance from the top left corner to the down right corner using one sampling widow with $Z \times W$ (height×width). And the amount of the window is only correlated to *Z*. The overlap height among the windows is *P*, thus the distance moved down is *L-P*. The amount of sampling widows, that is, the length of the image sequence *T* could be shown as:

$$T = \frac{H-L}{L-P} + 1 \quad (1)$$

where selections of L and P are playing crucial role to the ratio of face recognition. If there are not overlaps among sampling widows or the sampling height L is too little, the sampling window is not always correlated to the key facial features, and the complexity of the system is improved accordingly; if the sampling window is too large, the probability of cutting face features may be improved while sampling, here L is selected as:

$$L = \left[\frac{H}{20}\right], \quad P = L - 1 \tag{2}$$

One sequence of singular vectors could be obtained by distributing the singular values of each window's data sampled specially.

IV. FEATURE EXTRACTION OF FACE IMAGE

The feature location based on projection is adopted here for the minor of operation quantity as the prelude owing to the feature quantity of sets is too big and each set should use SVD to extract the singular value after one image sampled based on window method.

A. SVD theory

Doing singular value decomposition to one $m \times n$ gray image matrix A:

$$A = URV^T \tag{3}$$

Where U and V are two unit orthogonal matrixes, R is one diagonal matrix:

$$R = diag(\lambda_1, \lambda_2, \cdots) \tag{4}$$

If there are only K number of nonzero singular value, the matrix A could be decomposed as:

$$A = URV^T = \sum_{i=1}^{k} \lambda_i u_i v_i^T \tag{5}$$

Where u_i and v_i are the ith array of U and V separately, thus the singular value vectors of the matrix A is obtained:

$$S_{n\times 1} = (\lambda_1, \lambda_2, \cdots \lambda_k, 0, \cdots, 0)^T \tag{6}$$

The SVD of each real matrix is unique. SVD could be represented as numerical feature of a gray matrix A owing to the original image A is corresponding to only one singular value vector when it is arrayed as $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_k$.

B. Extracting SVD of face image

The inherent character of SVD shows that it can well obtained the features of one matrix and may used to extract the local features of human face. SVD is used to extract the features of the neighborhood matrix around eyes, nose and mouth to act as the main features of human face. The size of neighborhood matrix is correlated with the actual face. In this paper the neighborhood matrix are separately 13×17(left eye), 13×17(right eye), 15×15 （nose）, 13×21 （mouth）. According to the above mentioned that the central locations of the image in Fig.1(a1) as: Leye(24, 45), Reye(63, 45), Nose(42, 70), Mouth(42, 87), thus the top left corner coordinates of these four neighborhood matrixes in this image are separately (18, 37), (57, 37), (35,63) and (36, 60), and the SVD of the four local neighborhood matrixes are shown as Fig.5.

	1
1	-5.4984e-011
2	-2.6079e-011
3	1.0986e-011
4	3.7961e-011
5	0.022388
6	0.32032
7	1.048
8	1.2577
9	2.2094
10	3.383
11	18.222
12	29.891
13	40.537
14	67.313
15	132.51
16	236.36
17	7.1802e+006

(a)

	1
1	-5.4163e-011
2	2.6751e-012
3	2.6994e-011
4	1.0132e-010
5	0.38173
6	0.50098
7	0.97643
8	1.526
9	6.1569
10	8.5015
11	14.827
12	47.462
13	114.66
14	143.06
15	739.12
16	3607.3
17	6.2029e+006

(b)

	1
1	0.00055801
2	0.10646
3	0.41361
4	1.1441
5	1.6123
6	3.5592
7	9.6815
8	29.3
9	79.486
10	128.68
11	233.83
12	955.25
13	4843.8
14	22353
15	5.2802e+006

(c)

	1
1	-2.5748e-010
2	-2.5306e-011
3	-1.1006e-011
4	-7.2007e-012
5	4.7725e-012
6	3.0715e-011
7	6.8383e-011
8	5.5364e-010
9	0.71344
10	1.0055
11	2.1654
12	3.6595
13	17.14
14	23.001
15	29.659
16	105.24
17	139.52
18	1183.2
19	4223
20	37868
21	6.399e+006

(d)

Figure 5. Singular value features of the local matrix of (a) left eye, (b) right eye, (c) Nose and(d) Mouth

V. FEATURE MATCHING OF FACE RECOGNITION

Appropriate image matching is one of the important processes for face recognition. Firstly, matching the features of all facial components of the tested face and the one in the data-base after the local features of face are obtained, e.g., the matching process of left eye is as follows:

$$LeyeV = \sum_{i=1}^{n} (C[i] - D[i]) / D[i], \ (D[i] \neq 0) \qquad (7)$$

Among which $C[i]$ and $D[i]$ are the feature data of left eyes that extracted from input image and the one of data-base. Both them are arrayed in descending order, n is the amount of the feature value. For the same reason, the matching processes of LeyeV, ReyeV, NoseV and MouthV could be obtained. The finally matching could be gained by calculating the weighting sum of these matching values according to the roles of these facial components.

$$FaceV = LeyeV \times 0.3 + \mathrm{Re}\, yeV \times 0.3 + NoseV \times 0.2 + MouthV \times 0.2 \qquad (8)$$

The little of FaceV, the higher of the matching degree, thus the one made FaceV least in the face data-base is the optimum solution.

VI. Experimentation complexity analyzing

The calculation complexity of the method is moderate for 69 additions, 70 minus, 4 multiplications and 70 divisions are executed while calculating the FaceV of two images.

Setting the face image shown in Fig.1(a1) as the standard face, (b1) and (c1) are the objects to be tested while the former is the image of the same person's face of a1. The effect of this algorithm mentioned in this paper is tested by matching the features of b1 and c1 with that of a1, the statistical results are shown in Table.1.

Table 1. Matching degrees of similarity among b1, c1 and a1

Matching	LeveV	ReveV	NoseV	MouthV	FaceV
b1 & a1	22.9665	22.4146	105.8314	-1.1614	42.3228
c1 & a1	7.0298	-1.6405	408.6147	154.3264	114.2051

As is shown in the table, the FaceV of a1 and b1 is less than the one of a1 and c1, so a1 is better matching with the image of b1.

From the experimental result we see that eyes play important role among facial components in ascertaining of identity, so the weight coefficients are set 0.3, 0.3, 0.2 and 0.2 for left eye, right eye, nose and mouth when executing the final image matching. Rejection is not existing in this method because of this experiment adoption is to look for a minimum likeness degree. The matching process is speeded up obviously compared with traditional elastic model matching methods

VII. Conclusion

Aimed at the issue of low identification ratio of face recognition based on SVD, the algorithm based on extracting local key features and weigh matching is proposed. Experimental results show that this method not only calculating quickly, computing complexity small and easy to operate, but also effectively solve the issue of low recognition ratio of SVD.

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