A new algorithm using variations of image pixels to classify face images

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Abstract

When the interest operator is used as a feature extraction algorithm for face recognition, the algorithm may encounter the following problem: under complex imaging conditions such as varying facial expression, the feature extraction results of two corresponding blocks from two face images of the same subject may have low similarity. In order to address this problem, we propose a new algorithm in which an original image is first divided into a number of overlapping blocks and then the variations of pixel gray values of each block is calculated. Face recognition based on the new algorithm is able to obtain results with high similarity for the corresponding blocks from two images of the same subject. Experimental results on the FERET face database show that the combination of the proposed algorithm and 2DPCA or 2DFLD offers significant accuracy improvement over the combination of the conventional interest operator and 2DPCA or 2DFLD.

1. Introduction

Face recognition is one important branch of biometric research. Complex circumstances such as various pose, face expression, and lighting condition make face recognition challenging. Indeed, to obtain features with strong identification ability and have robustness to the complex circumstance is significant for face recognition. Nowadays some statistics-based technologies such as a robust face matching method under different lighting conditions proposed by Chyuan [1] and a robust method for various face expression proposed by Hossein [2] have solved the problem in a way, but when the change is tremendous, the recognition accuracy may also be low.

The interest operator has been used in the area of signal processing and digital image processing. It is first proposed by Moravec [3] for the feature extraction of automatic robot navigation system in 1981. Then it is used by Nasrabadi [4] for the stereo vision correspondence and used by Wang [5] for the automatic target recognition. Caleanu is the first to exploit the interest operator for face recognition [6]. After that, Zhao proposed a kind of reformative interest filter for face recognition [7].

Face recognition using the interest operator may encounter the following problem: The interest operator can not describe the variations among the adjacent pixels in different blocks as the blocks are independent with each other, so when the circumstance is complex, the feature extraction results of the conventional interest algorithm on two corresponding blocks from two face images of the same subject may have low similarity. In other words, there may be much difference between the results of the two corresponding blocks obtained using the interest operator. It is difficult for face recognition using the interest operator to obtain high accuracy under complex circumstance.

In this paper, a new algorithm is proposed in which the images are first divided into overlapping blocks and then the interest operator is applied to each block to compute the variations of pixel gray values. The rationale of the proposed algorithm is as follows: since different blocks overlap one another, it can smooth the change of different face images of the same subject, so it will be more similar for the results of the two corresponding blocks of two face images generated from the same subject than the results of the two corresponding blocks obtained using the conventional interest operator. As a result, we may obtain higher accuracy by using the proposed algorithm. A number of experiments on FERET database show that the combination of the proposed algorithm and 2DPCA or 2DFLD obtains higher accuracy than the combination of the conventional interest operator and 2DPCA or 2DFLD.

2. The conventional interest algorithm

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The conventional interest operator is used to find the directional variances of image pixels in the horizontal, vertical and both diagonal directions for each block of an image [5].

The conventional interest operator can be described as follows: the mean of a block is calculated by Eq.(1) and the center variance σ^2 is calculated by Eq. (2). σ_0^2 , σ_{45}^2 , σ_{90}^2 and σ_{135}^2 are used to calculate the directional variances in horizontal, diagonal -45° , vertical and diagonal -135° respectively. σ_0^2 , σ_{45}^2 , σ_{90}^2 and σ_{135}^2 are respectively calculated by Eq.(3), (4), (5) and (6).

$$u = \frac{1}{P \times Q} \sum_{x=1}^{P} \sum_{y=1}^{Q} p(x, y) \tag{1}$$

$$\sigma^2 = \frac{1}{P \times Q} \sum_{x=1}^{P} \sum_{y=1}^{Q} [p(x, y) - u]^2 \tag{2}$$

$$\sigma_0^2 = \frac{1}{P \times Q} \sum_{x=1}^{P-1} \sum_{y=1}^{Q} [p(x+1, y) - p(x, y)]^2 \tag{3}$$

$$\sigma_{45}^2 = \frac{1}{P \times Q} \sum_{x=1}^{P-1} \sum_{y=1}^{Q-1} [p(x+1, y) - p(x, y+1)]^2 \tag{4}$$

$$\sigma_{90}^2 = \frac{1}{P \times Q} \sum_{x=1}^{P} \sum_{y=1}^{Q-1} [p(x, y+1) - p(x, y)]^2 \tag{5}$$

$$\sigma_{135}^2 = \frac{1}{P \times Q} \sum_{x=1}^{P-1} \sum_{y=1}^{Q-1} [p(x+1, y+1) - p(x, y)]^2 \tag{6}$$

Suppose that the size of each block is P×Q and $\{p(x, y), 1 \le x \le P, 1 \le y \le Q\}$ refers to the gray value of the point (x, y) in a block. If an image is of size of 80×80, and we divide it with 2×2 blocks. We calculate $\sigma^2, \sigma_0^2, \sigma_{45}^2, \sigma_{90}^2, \sigma_{135}^2$ for each block, so we can get 1600(40×40) blocks for each direction. Put them together, the conventional interest operator will obtain an 8000-dimensional feature (40×200) for an original face image. We can perform face recognition using these features extracted from the original face images.

3. The new algorithm

Face recognition using the conventional interest operator has the following shortcoming: under the circumstances of various pose, facial expressions, and lighting condition, there may be much difference between a block of one face image of a subject and the corresponding block of another face image of the same subject. This will be disadvantageous for face recognition using the conventional interest operator to obtain high accuracy. In order to overcome this disadvantage, we propose a new algorithm for face recognition. The new algorithm first divides each image into a number of overlapping blocks, and then the interest operator is applied to each block to compute the variations of pixel gray values. One can classify the samples using the obtained results of face images.

The proposed algorithm can be shown more clearly by the following example: if we divide the original image into a number of 4×4 overlapping blocks and half of each block is overlapped by its adjacent blocks, then a 80×80 image will obtain 1521 (=39×39) blocks for each direction. As a result, the result of the original image will form a 7605-dimensional vector (39×195).

Features obtained using the conventional interest operator or our algorithm is usually quite high-dimensional. Linear feature extraction methods such as 2DPCA or 2DFLD can be used to transform the results into lower-dimensional feature. For detail of 2DPCA and 2DFLD, please see [8-14].

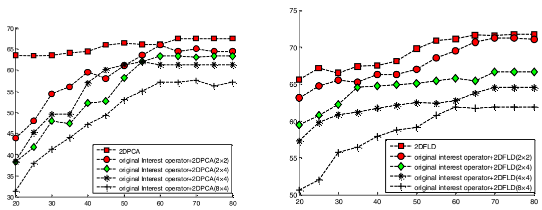
4. Experiments

In this section, we conduct experiments on the FERET face database in which there are 200 subjects, each subject provides 7 face images with various lighting condition, pose and face expression. The size of each image is 80×80. We conduct experiments using several different schemes. All of our experiments are carried out based on Matlab 7 and a PC machine with P4 3 GHz CPU and 512 MB RAM memory.

4.1 Experiment on the combination of 2DPCA or 2DFLD and the conventional interest operator

In this experiment, we will compare the following approaches: 2DPCA, 2DFLD and the combination of 2DPCA or 2DFLD and the conventional interest operator. The combination of 2DPCA or 2DFLD and the conventional interest operator works as follows: first, the conventional interest operator is applied to every image block. Note that each block produces five values, i.e. $\sigma^2, \sigma_0^2, \sigma_{45}^2, \sigma_{90}^2, \sigma_{135}^2$. Hence, each value such as σ^2 of all the blocks can form a matrix. After the conventional interest operator is carried out for all blocks of an image, we can obtain five matrices. Then 2DPCA or 2DFLD is used to extract features from the combination of the five matrices of every image.

We compute the similarity between two face images using $\delta(x,y)=\frac{x^T y}{\|x\|\times\|y\|}$, where x, y are two one-dimensional vectors representing feature extraction results of the two face images. We classify the samples according to the similarities. We randomly choose three samples of each subject as the training samples and regard the remaining four samples as the test samples. 2×2, 2×4, 4×4 and 8×4 blocks are applied to the approaches and the dimension varies from 20 to 80. Fig.1 presents recognition accuracies of different approaches.



(a) (b)

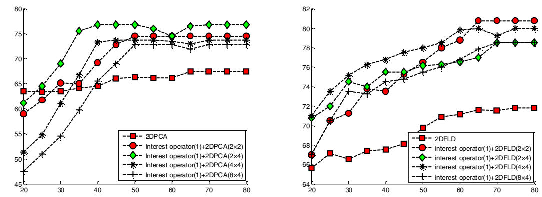
Fig.1. The results for the combination of 2DPCA and the conventional interest operator shown in (a) and the combination of 2DFLD and the conventional interest operator shown in (b)

Fig.1 shows that the combination of 2DPCA and the conventional interest operator is not able to obtain higher accuracy than 2DPCA, and the combination of 2DFLD and the conventional interest operator is not able to obtain higher accuracy than 2DFLD, either.

4.2 Experiment on Scheme 1 of our algorithm

In this experiment, we calculate $\sigma^2, \sigma_0^2, \sigma_{45}^2, \sigma_{90}^2, \sigma_{135}^2$ for each pixel. In other word, our approach allows two adjacent blocks to overlap one another with the maximum extent, so, there will be only one line or one row not overlapped by the adjacent blocks at one time. Therefore, an 80×80 image will also get an 80×80 target image for each direction. Note that we will extract 32000-dimensional feature from an 80×80 image by using the Scheme 1 of our algorithm, high computational cost is a disadvantage of this scheme. 2×2, 2×4, 4×4 and 8×4 blocks are also applied to the scheme. Fig. 2 shows the experimental results of different approaches.

From Fig.2 we can see that the combination of 2DPCA and Scheme 1 of our algorithm can offer significant accuracy improvement over 2DPCA, and the combination of 2DFLD and Scheme 1 of our algorithm can also greatly outperforms 2DFLD.

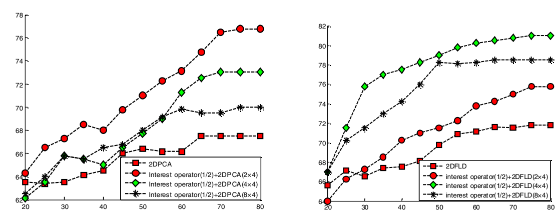


(a) (b)

Fig.2. The results for the combination of 2DPCA and Scheme 1 of our algorithm shown in (a) and the combination of 2DFLD and Scheme 1 of our algorithm shown in (b)

4.3 Experiment on Scheme 2 of our algorithm

Scheme 2 of our algorithm refers to applying our algorithm to 2×4, 4×4 and 8×4 blocks for which half of the region of a block is overlapped by the adjacent block. The experimental results of Scheme 2 are shown in Fig.3:



(a) (b)

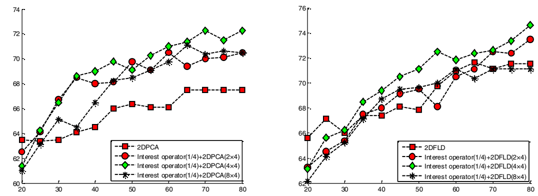
Fig.3 The results for the combination of 2DPCA and Scheme 2 of our algorithm shown in (a) and the combination of 2DFLD and Scheme 2 of our algorithm shown in (b)

From Fig.3, we can see that the combination of Scheme 2 of our algorithm and 2DPCA can get much higher recognition accuracy than 2DPCA , and the combination of Scheme 2 of our algorithm and 2DFLD also performs much better than 2DFLD.

4.4 Experiment on Scheme 3 of our approach

Scheme 3 of our algorithm refers to applying our algorithm to 2×4, 4×4 and 8×4 blocks for which one fourth of the region of a block is overlapped by the adjacent block. The experimental results are shown in Fig.4:

From Fig.4 we can see that Scheme 3 of our algorithm obtains lower accuracy than Scheme 1 and Scheme 2 of our algorithm. The combination of Schemes 1, 2 and 3 of our algorithm and 2DPCA or 2DFLD all outperform 2DPCA or 2DFLD, respectively.



(a) （b）

Fig.4 The results for the combination of 2DPCA and Scheme 3 of our algorithm shown in (a) and the combination of 2DFLD and Scheme 3 of our algorithm shown in (b)

In order to see the experimental results of Sections 4.1-4.4 more clearly, we use Table 1 to summarize the results, including the highest recognition accuracy of each scheme. Table 1 also shows the time taken by the schemes and the feature extraction time taken by 2DPCA or 2DFLD when the highest recognition accuracies are obtained.

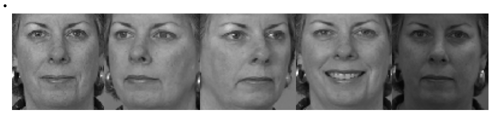
Table.1 Experimental results of all the schemes

	The highest recognition accuracy (%)	Time for the schemes (s)	Feature extraction Time(s)
2DPCA	67.5		276.1
2DFLD	71.75		273.5
IO+2DPCA	65	349.7	232.3
IO+2DFLD	71.25	349.7	229.8
I(1)+2DPCA	76.75	1354.6	649.4
I(1)+2DFLD	80.75	1033.8	589.6
I(1/2)+2DPCA	76.75	621.4	388.03
I(1/2)+2DFLD	81	593.9	356.8
I(1/4)+2DPCA	72.25	477.1	310.7
I(1/4)+2DFLD	74.625	477.1	306.2

IO represents the conventional interest operator. I(1),I(1/2) and I(1/4) stand for Schemes 1,2 and 3 of our algorithm, respectively. From Table 1, we can see that the combination of Scheme 1, 2, 3 of our algorithm and 2DPCA or 2DFLD are all able to obtain higher recognition accuracy than the combination of 2DPCA or 2DFLD and the conventional interest operator. Scheme 1 performs as better as Scheme 2 of our algorithm. However, among all the schemes, the combination of Scheme 1 of our algorithm and 2DPCA or 2DFLD takes the longest time to implement the scheme and the feature extraction. Indeed, the combination of 2DPCA and our algorithm obtains a maximum improvement in accuracy of 11.75% in comparison with the combination of 2DPCA and the conventional interest operator, and obtains a maximum improvement in accuracy of 9.25% in comparison with 2DPCA. The combination of 2DFLD and our algorithm obtains a maximum improvement in accuracy of 9.75% in comparison with the combination of 2DFLD and the conventional interest operator, and obtains a maximum improvement in accuracy of 9.25% in comparison with 2DFLD.

4.5 Robustness analysis of the new algorithm

At this section, we choose five images for each subject. Among them images (b), (c), (d) and (e) have some change in pose, facial expression and lighting condition from image (a). The five images of one people from the FERET face database are shown in Fig.5:



(a) (b) (c) (d) (e)

Fig.5.The five pictures we choose for one people in FERET

In Fig.5, image(b), (c) have some pose change from image(a), image (d) has some expression change form image (a), image (e) has some lighting condition change from image (a). We compute the similarities between images (b), (c), (d), (e) and image (a) of each subject using $\delta(x,y)=\dfrac{x^T y}{\|x\|\times\|y\|}$. Note that the interest operator produces five resultant images for each original image. We concatenate the five resultant images of every original image and convert the concatenation result into a vector, which we call the vector corresponding to the resultant images. We also calculate the similarities between the vector corresponding to the resultant images of the original face image (a) and those corresponding to the resultant images of the original face images (b), (c), (d), (e) for each scheme. Then the means of the similarities for all the subjects in FERET database are shown in Table 2. The blocks in all the experimental schemes have the same size of 8×4. The second to fifth columns respectively represent the means of the similarities between (a) and (b), (c), (d), (e).

Table.2. Similarities between (a) and (b), (c), (d), (e)

	2	3	4	5
OI	0.95639	0.95882	0.96397	0.94361
IO	0.95314	0.9502	0.98437	0.93702
I(1)	0.96422	0.9658	0.9899	0.95361
I(1/2)	0.96311	0.96269	0.98953	0.95531
I(1/4)	0.95361	0.96168	0.98442	0.94693

OI represents the similarities between the original images (b), (c), (d), (e) and the original image (a). IO, I(1), I(1/2) and I(1/4) respectively represent the similarities in each scheme between the one-dimensional vectors of the resultant images of the original face image (a) and the one-dimensional vectors of the resultant images of the original face images (b), (c), (d), (e). From the data above, we can see, Scheme 1, 2 and 3 are all robust for the change in pose, facial expression and lighting condition because the similarities in Line 2, Line 3, Line 4 and Line5 for the schemes are higher than the data in Line2, Line 3, Line 4 and Line 5 of OI. The performance of Scheme 1 is as better as Scheme 2. The highest similarity for Scheme 1 is 0.9899 and the highest similarity for Scheme 2 is 0.98953, while the highest similarity for OI is 0.96397. The conventional interest operator is robust for the change of facial expression. Indeed, the similarity in Line 4 of IO reaches 0.98437 and the data for OI is 0.96397.

The data in Table.2 can prove why the schemes of our algorithm can obtain higher recognition accuracy than the conventional interest operator.

5. Conclusion

The new algorithm proposed in this paper first divides an original image into a number of overlapping blocks and then computes the variations of pixel gray values of each block. When the new algorithm is applied to two corresponding blocks from two images of the same subject, the results of the two blocks have higher similarity in comparison with the results obtained using the conventional interest operator. Experimental results on the FERET database show that the combination of the proposed algorithm and 2DPCA or 2DFLD obtains significant accuracy improvement over the combination of the conventional interest operator and 2DPCA or 2DFLD. Especially, Scheme 2 of our algorithm performs very well in face recognition.

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