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Improving the interest operator for face recognition

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ABSTRACT

When the conventional interest operator is used as the feature extraction procedure of face recognition, it has the following two shortcomings: first, though the purpose of the conventional interest operator is to use the intensity variation between neighboring pixels to represent the image, it cannot obtain all variation information between neighboring pixels. Second, under varying lighting conditions two images of the same face usually have different feature extraction results even though the face itself does not have obvious change. In this paper, we propose two new interest operators for face recognition, which are used to calculate the pixel intensity variation information of overlapping blocks produced from the original face image. The following two factors allow the new operators to perform better than the conventional interest operator: the first factor is that by taking the relative rather than absolute variation of the pixel intensity as the feature of an image block, the new operators can obtain robust block features. The second factor is that the scheme to partition an image into overlapping rather than non-overlapping blocks allows the proposed operators to produce more representation information for the face image. Experimental results show that the proposed operators offer significant accuracy improvement over the conventional interest operator.

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1. Introduction

Since the interest operator was first proposed, it has been wildly used to represent image or target feature. For example, Moravec (1981) used an interest operator to compute the intensity variances in the horizontal, vertical and both diagonal directions for each pixel point in an image and selected the minimum of these values as the variance of that point. Nasrabadi and Choo (1994) used the interest operator in the stereo vision correspondence. In Nasrabadi and Choo (1994), the interest operator was applied to all image blocks and the point having the local maximal variance in each local block was selected as the so-called interesting point of that block. Căleanu, Huang, Gui, Tiponu, and Maranescu (2007), Căleanu (2000), Căleanu (2001), Zhao, Huang, and Sun (2004) and Zhao (2007) used the interest operator to extract features from face images. The interest operator was also exploited for target recognition (Haber & Modersitzki, 2004). Generally speaking, the interest operator for recognition can be viewed as a feature extraction algorithm that calculates variation information in different directions of the image pixel intensity. Note that when the interest operator is applied to face recognition, the first step is to divide each image into the same number of blocks with a fixed size. Then feature extraction is performed for each block by using the interest operator. Finally, one can treat the feature extraction results of all the blocks of a face image as the representation of this image and can classify face images using the representation and a classifier.

It should be pointed out that complex imaging conditions such as varying pose, facial expression and lighting conditions may restrict the ability of the interest operator. Actually, complex imaging conditions degrade performances of most of face recognition techniques (Adini, Moses, & Ullman, 1997). In addition, the human face is a deformable object and a face can produce different deformations at different times, resulting in various facial expressions. Consequently, there may be much difference between a block of one image of a face and the same block of another image of the same face, if the two images are associated with different poses or facial expressions. Face recognition using the conventional interest operator, therefore, has the following shortcoming: the feature extraction results of different images of the same face might have much difference. Another shortcoming of the conventional interest operator stems from the algorithm itself. Under varying lighting conditions the algorithm usually also produces different feature extraction results for the same face, even if the face itself does not have any change in pose and expression. This is because varying lighting conditions produce different intensity values for the image pixel. For example, high intensity lighting usually produces

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high intensity value for the pixel and consequently the variation between two neighboring pixels usually also appears to be high. On the other hand, low intensity lighting usually produces low intensity value for the pixel and consequently the variation between two neighboring pixels is also low. As a result, when we compare the feature extraction results of two images that are obtained under the high and low intensity lighting conditions, a low similarity may be produced. The third shortcoming of the conventional interest operator is that it cannot obtain all variations between neighboring pixels. Indeed, since the conventional interest operator is applied to only pixels within an image block, the conventional interest operator is not able to compute the variations between two neighboring pixels that are located in two blocks, respectively. This is illustrated by Fig. 1.

In this paper, in order to overcome the shortcomings of the conventional interest operator, we propose to exploit new operators and the overlapping block partition scheme for face recognition. The rationale of the proposed approach is as follows: first, because the improved interest operator takes the relative rather than absolute variation of image pixel intensity as the features of the face image, this approach can produce more stable face features for the same face than the conventional interest operator, especially under varying lighting conditions. This is helpful for obtaining a satisfactory classification accuracy. Second, since in our approach different blocks overlap one another, our approach allows intensity variations between all pixels to be provided whereas the conventional interest operator cannot do so. Experimental results illustrate that our approach can produce a higher accuracy in comparison with the conventional interest operator. Experiments also show that a linear feature extraction approach can be combined with the proposed interest operators to obtain further performance improvement.

2. The conventional interest operator

As mentioned above, the conventional interest operator evaluates the variation of image pixels in the horizontal, vertical and both diagonal directions for each block of an image. The conventional interest operator can be described as follows: it calculates the mean μ and the center variance σ^2 of a block using (1) and (2), respectively. It calculates $\sigma_0^2, \sigma_{45}^2, \sigma_{90}^2$ and σ_{135}^2, which respectively stand for the intensity variations of block pixels in horizontal, diagonal 45°, vertical and diagonal 135° directions, using (3)–(6), respectively.

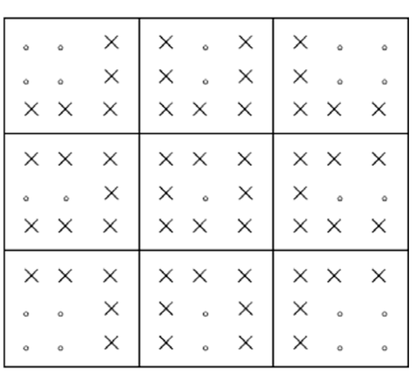

Fig. 1. Illustration of the non-overlapping block partition scheme used for the conventional interest operator. This figure shows that an image is divided into nine non-overlapping blocks each consisting of a number of pixels. For a block, we denote the boundary pixels that adjoin another block by '×' and we denote the other pixels by "∘". Note that for two '×' pixels respectively located in two blocks, even if they are neighbors, the pixel intensity variation of the two pixels cannot be obtained by the conventional interest operator.

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

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

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

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

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

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

Hereafter we suppose that the size of each block is $P \times Q$ and $p(x,y)(1 \leqslant x \leqslant P, 1 \leqslant y \leqslant Q)$ represents the pixel intensity of the point (x,y) in a block. Fig. 2 shows the feature extraction results of a face image obtained using the conventional interest operator. From Fig. 2, we can clearly see that if two original images of the same face are obtained under varying conditions, their resultant images may have obvious difference.

3. Description of our approach

Our approach consists of two components, an overlapping block partition scheme and an improved interest operator. The goal of our approach is to improve image presentation ability of the conventional interest operator. The basic idea for improving the interest operator is to take the relative variation of the gray intensity as features of the image block. Based on this idea, we develop two new interest operators as shown in the following.

3.1. Improved interest operator 1

Improved interest operator 1 is defined as follows:

$$\sigma^2 = \frac{1}{P \times Q} \sum_{x=1}^{P} \sum_{y=1}^{Q} \frac{[p(x,y) - u]^2}{(u + c_1)^2} \tag{7}$$

$$\sigma_0^2 = \frac{1}{P \times Q} \sum_{x=1}^{P-1} \sum_{y=1}^{Q} \frac{[p(x+1,y) - p(x,y)]^2}{(u + c_1)^2} \tag{8}$$

$$\sigma_{45}^2 = \frac{1}{P \times Q} \sum_{x=1}^{P-1} \sum_{y=1}^{Q-1} \frac{[p(x+1,y) - p(x,y+1)]^2}{(u + c_1)^2} \tag{9}$$

$$\sigma_{90}^2 = \frac{1}{P \times Q} \sum_{x=1}^{P} \sum_{y=1}^{Q-1} \frac{[p(x,y+1) - p(x,y)]^2}{(u + c_1)^2} \tag{10}$$

$$\sigma_{135}^2 = \frac{1}{P \times Q} \sum_{x=1}^{P-1} \sum_{y=1}^{Q-1} \frac{[p(x+1,y+1) - p(x,y)]^2}{(u + c_1)^2} \tag{11}$$

where u is also defined by (1) and c_1 is a positive constant. Indeed, the new operator as defined in (7)–(11) produces the relative rather than absolute variation of the pixel intensity by dividing the result of the conventional interest operator by a quantity associated with the mean of the pixel intensity. The difference between improved interest operator 1 and the conventional interest operator is as follows. As presented above, varying lighting condition is one typical factor that makes two corresponding pixels from two images of the same face have quite different intensities. As a result, under varying lighting condition, two corresponding image blocks from two images of the same face usually appear to have different intensity variations. The conventional interest operator, therefore, usu-

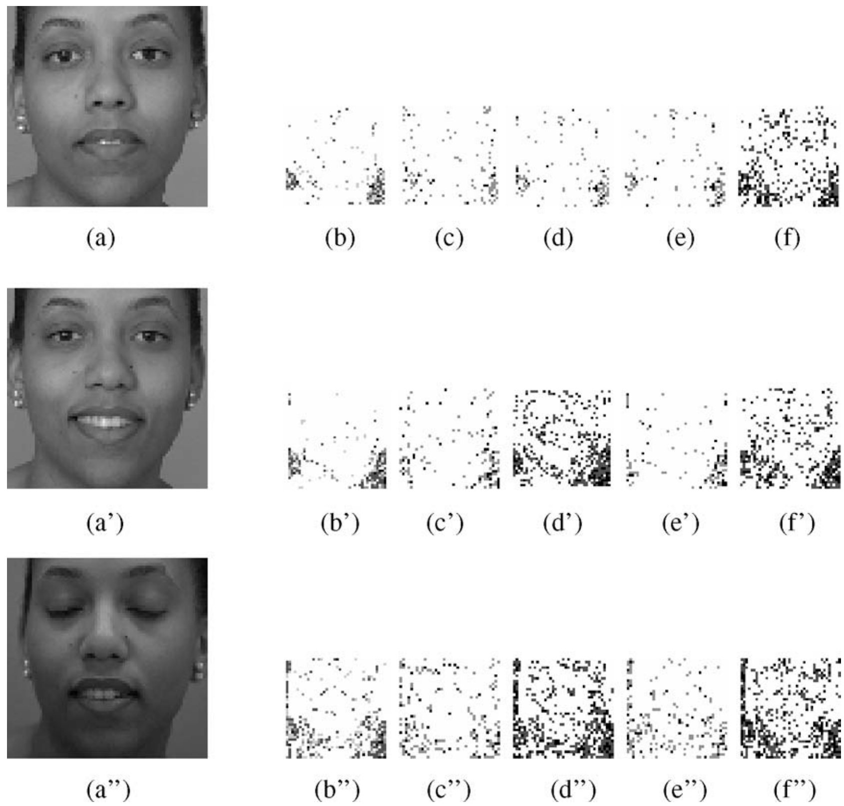

Fig. 2. The original face and resultant images obtained using the conventional interest operator. Each row shows the face and resultant images. For example, (b), (c), (d), (e) and (f) respectively stand for the resultant images on $\sigma^2, \sigma_0^2, \sigma_{45}^2, \sigma_{90}^2, \sigma_{135}^2$ of the face image shown in (a). The original face image is first divided into a number of non-overlapping 2 by 2 blocks and then the conventional interest operator is implemented for each image block.

ally does not perform well in producing stable features for the same face under varying lighting condition. However, by using the relative variation of the pixel intensity as shown in (7)–(11) as the feature of the face image, improved interest operator 1 is able to produce more stable features for the same face under varying lighting condition. The use of constant c_1 can prevent the operator from being unfeasible in the case where the mean of the pixel intensity is zero.

3.2. Improved interest operator 2

Improved interest operator 2 is designed as follows:

$$\sigma^2 = \frac{1}{P \times Q} \sum_{x=1}^{P} \sum_{y=1}^{Q} \frac{|p(x,y) - u|}{u + c_2} \tag{12}$$

$$\sigma_0^2 = \frac{1}{P \times Q} \sum_{x=1}^{P-1} \sum_{y=1}^{Q} \frac{|p(x+1,y) - p(x,y)|}{u + c_2} \tag{13}$$

$$\sigma_{45}^2 = \frac{1}{P \times Q} \sum_{x=1}^{P-1} \sum_{y=1}^{Q-1} \frac{|p(x+1,y) - p(x,y+1)|}{u + c_2} \tag{14}$$

$$\sigma_{90}^2 = \frac{1}{P \times Q} \sum_{x=1}^{P} \sum_{y=1}^{Q-1} \frac{|p(x,y+1) - p(x,y)|}{u + c_2} \tag{15}$$

$$\sigma_{135}^2 = \frac{1}{P \times Q} \sum_{x=1}^{P-1} \sum_{y=1}^{Q-1} \frac{|p(x+1,y+1) - p(x,y)|}{u + c_2} \tag{16}$$

where u is still defined by (1) and c_2 is a positive constant. Differing from improved interest operator 1, the second improvement operator takes as the feature of an image block the result of the conventional interest operator divided by the sum of the mean of the pixel intensity and c_2. The use of c_2 enables the operator to be workable in the case where the mean of the pixel intensity is zero. Improved interest operator 2 also has the similar advantages to improved interest operator 1.

3.3. Overlapping block partition scheme

As mentioned above, though the conventional interest operator was developed to calculate the pixel intensity variation, not all variation information between neighboring pixels could be obtained. Indeed, the conventional interest operator cannot calculate the variations between two neighboring pixels respectively located in two blocks as shown in Fig. 1. In order to overcome this drawback of the conventional interest operator, we propose to partition an image into a number of overlapping blocks and to extract features from each block by using either of the two interest operators respectively presented in Sections 3.1 and 3.2.

Note that in our partition scheme two horizontally neighboring blocks overlap one another and so do two vertically neighboring blocks. Fig. 3 shows that how an original 6×6 image is partitioned into four overlapping image blocks each having the size of 4×4. Here each rectangle unit represents a pixel. The overlapping region is represented by the shadow, which shows that half of each block is overlapped by a neighboring block. Our approach implements improved interest operator 1 (or improved interest operator 2) for each image block produced by the overlapping block partition scheme.

Advantages of our approach can be described as follows. First, because our approach takes the relative rather than absolute variation of the pixel intensity as the feature of an image block, the feature extraction result appears to be less affected by the lighting

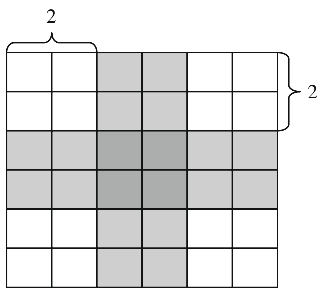

Fig. 3. Illustration of the scheme to partition an image into overlapping image blocks. The overlapping region is represented by the shadow. Each image block is of size of 4×4. Half of every block is overlapped by a neighboring block. For example, half of the 4×4 image block located in the left top is overlapped by its right neighbor image block. For the same block, its down neighbor 4×4 block also overlaps half of its size.

condition than the conventional interest operator. This helps our approach obtain more robust features than the conventional interest operator. Second, our approach allows information of the intensity variation of all neighboring pixels to be obtained due to the overlapping partition scheme, whereas the conventional interest operator cannot do so. Fig. 4 shows an original face image and the feature extraction result of this image obtained using improved interest operator 1.

The overlapping block partition scheme can be shown more clearly by the following example: if the original image is represented by an 80×80 matrix and we partition the original image into a number of 4×4 overlapping blocks and half of each block is overlapped by a neighboring block, we will obtain 1521 overlapping image blocks. When we calculate each of the $\sigma^2, \sigma_0^2, \sigma_{45}^2, \sigma_{90}^2, \sigma_{135}^2$ values for all the 1521 image blocks of the original image, the result that we obtain is a 1521-dimensional vector. The vector can be also shown as a 39×39 matrix as illustrated in Fig. 4. Since each block has its own five values $\sigma^2, \sigma_0^2, \sigma_{45}^2, \sigma_{90}^2, \sigma_{135}^2$, the feature extraction result of the original image can be regarded as five 1521-dimensional vectors or five 39×39 matrices. Concatenating these one-dimensional vectors, we can obtain a 7605-dimensional vector. More generally, if the original image is an $m \times n$ matrix and we partition the original image into a number of $s \times t$ overlapping blocks and half of each block is overlapped by a neighboring block, $(2m/s - 1) \times (2n/t - 1)$ image blocks will be generated. As a result, for this original image, the feature extraction result produced by our approach will be a $5(2m/s - 1) \cdot (2n/t - 1)$-dimensional vector.

Similar to the features obtained using the conventional interest operator, the features obtained using our approach are also usually very high-dimensional. However, as shown in Section 5, linear feature extraction procedures such as 2DPCA (two-dimensional PCA) or 2DFLD (two-dimensional Fisher discriminant analysis) (Cho, Chang, Kim, & Lee, 2006; Kongsontana & Rangsanser, 2005; Mutelo, Khor, Woo, & Dlay, 2006; Nhat & Lee, 2005; Sanguansat, Asdornwised, Jitapunkul, & Marukatat, 2006; Wang, Wang, Zhang, & Feng, 2005; Xu, Zhang, Yang, & Yang, 2008; Yang, Zhang, Frangi, & Yang, 2004; Yang et al., 2004) can be used to transform the feature extraction results of the interest operator into lower-dimensional features.

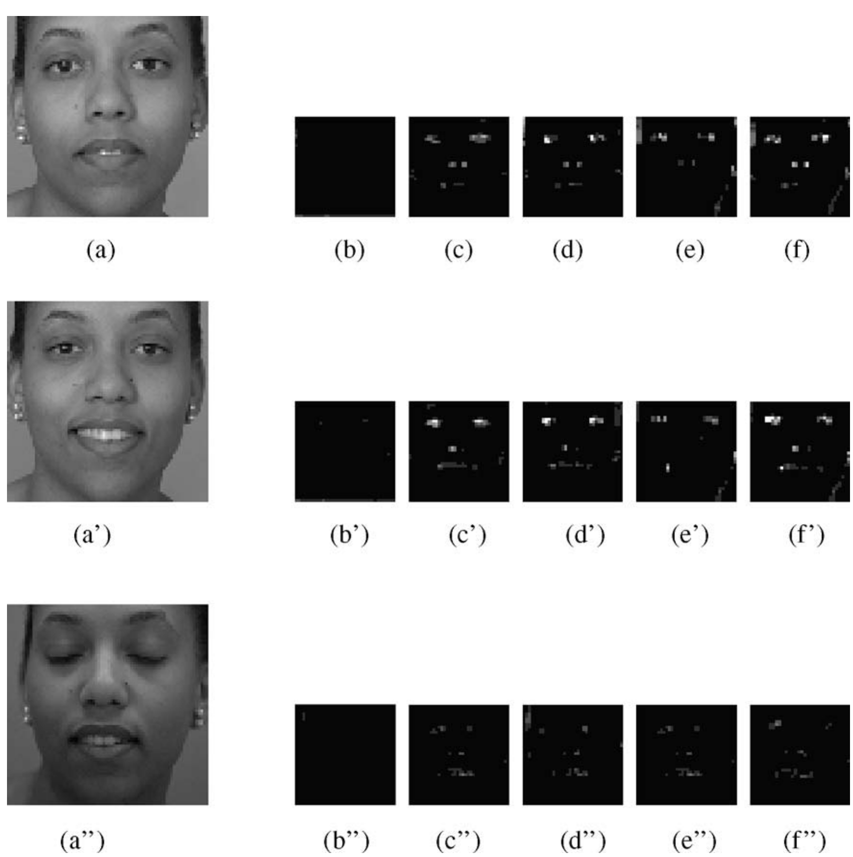

Fig. 4. The original face image and the resultant images obtained using improved interest operator 1 with $c_1 = 10$. Each row shows a face image and the resultant images. For example, (b), (c), (d), (e) and (f) respectively stand for the resultant images on $\sigma^2, \sigma_0^2, \sigma_{45}^2, \sigma_{90}^2, \sigma_{135}^2$ of the face image shown in (a). Note that the original face image is first divided into overlapping 4 by 4 blocks and then improved interest operator 1 is implemented for each image block. Half of an image block is overlapped by a neighboring image block.

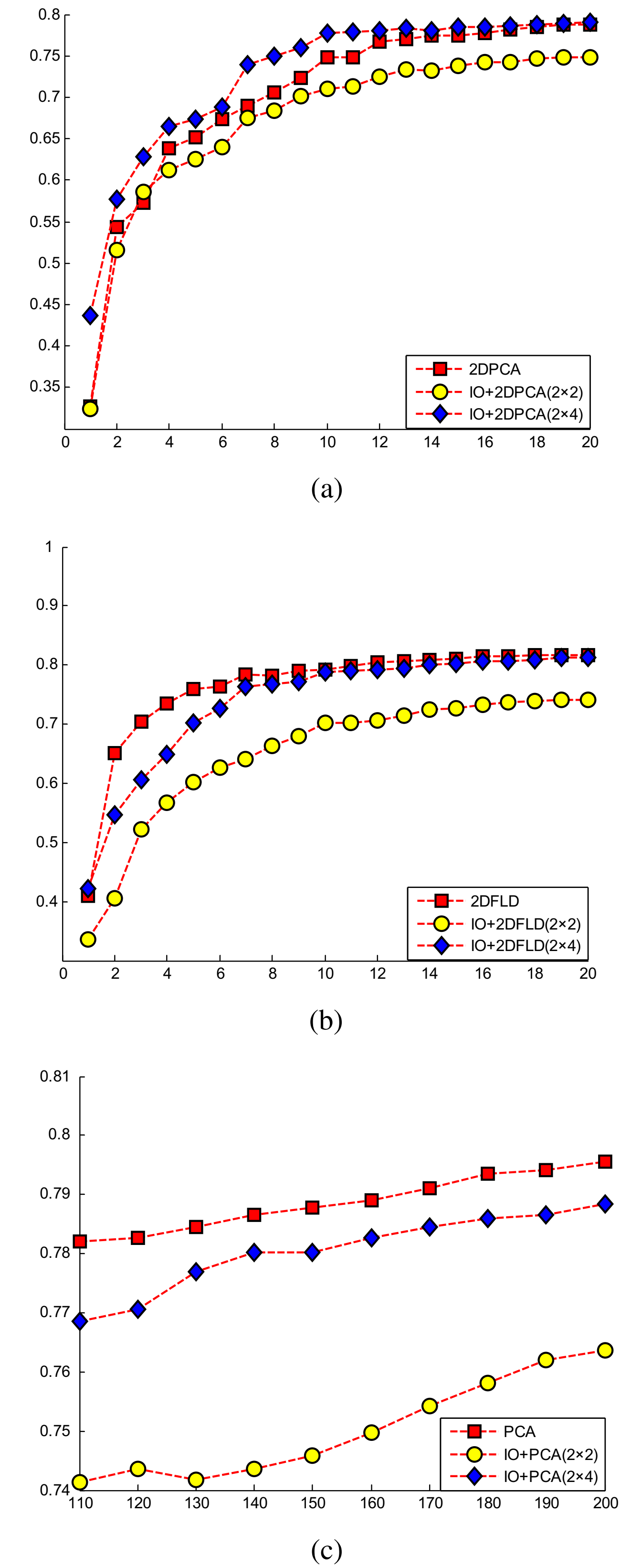

Fig. 5. Face recognition results on the AR database obtained by different linear feature extraction procedures combined with or without the conventional interest operator. (a) Classification right rate associated with 2DPCA, (b) classification right rate associated with 2DFLD and (c) classification right rate associated with PCA. The horizontal coordinate represents the number of the transforming axes of the linear feature extraction procedure used for feature extraction and the vertical coordinate represents the classification accuracy. The horizontal and vertical coordinates of Figs. 6, 7, 9–11 are same as this figure.

Table 1
Experimental result comparison of our approach and other approaches on the AR face database.

	Best accuracy(%)	Mean of the accuracy(%)	Size of the block
2DPCA	78.8	70.1	
2DFLD	81.7	76.4	
PCA	79.6	78.9	
IO + 2DPCA	79.0	69.5	2×4
IO + 2DFLD	81.3	70.0	2×4
IO + PCA	78.8	76.0	2×4
OIIO1 + 2DPCA	81.7	75.7	2×4
OIIO1 + 2DFLD	84.2	78.0	2×4
OIIO1 + PCA	82.1	81.4	2×4
OIIO2 + 2DPCA	91.9	82.2	2×4
OIIO2 + 2DFLD	93.5	86.7	2×4
OIIO2 + PCA	91.9	90.1	2×4

4. More discussion on improved and the conventional operators

In this section we will compare improved interest operators with conventional interest operator and some other algorithms that exploit gradient information of the image. First, we analyze the relationship and difference between the conventional interest operator and the gradient operator. As presented above, the interest operator computes the pixel intensity variation in different directions. Gradient operators also evaluate the pixel intensity variation. The difference between the interest operator and the gradient operator are as follows: a gradient operator produces a vector i.e. gradient vector that uses two components to indicate the gradient whereas the interest operator obtains only scalar values. The square-root of the squared sum of the two components of the gradient vector is usually used to denote the magnitude value of the gradient. The similarity between the interest operator and the gradient operator is as follows: for the conventional interest operator, σ_{45}^2 and σ_{135}^2 as defined in (4) and (6) act as the mean of the squares of the two components of the Roberts gradient operator (Gonzalez & Woods, 1987), respectively. Additionally, according to the definition of the gradient, σ_0^2 and σ_{90}^2 as defined in (3) and (5) can also be respectively regarded as the mean of the squares of two components of a gradient operator. Consequently, we can conclude that the interest operator and the gradient operator provide image gradient information in different ways. The interest operator aims at calculating 'average' gradient information in different directions of an image block, whereas the gradient operator provides gradient information of each image pixel in the form of a vector. Gradient operators and improved gradient operators have been applied to recognition problems (Gao & Leung, 2002; Haber & Modersitzki, 2004; TakaÂcs, 1998; Wei & Lai, 2006) and image matching problems (Ando, 2000; Wolfson & Rigoutsos, 1997).

Approaches exploiting image gradient information for recognition can be classified into two classes. The first class of approaches exploits the image gradient information itself to perform recognition. The approaches proposed in Haber and Modersitzki (2004) and Wei and Lai (2006) as well as the conventional interest operator are examples of the first class. In Haber and Modersitzki (2004) and Wei and Lai (2006), 'normalized gradient' and 'relative gradient' were respectively used as image features. In Wei and Lai (2006), the magnitude of the conventional gradient of a pixel point was first divided by the sum of a constant and the maximum magnitude of the gradient in an image block. Then the division result was taken as 'relative gradient' of the pixel point. The second class of approaches firstly exploits the image gradient information to produce image edges and then employs image edges to perform recognition. The rationale of the second class of approaches is that edge information is a useful object representation feature (Gao & Leung, 2002). The approaches used in Gao and Leung (2002), Ta-

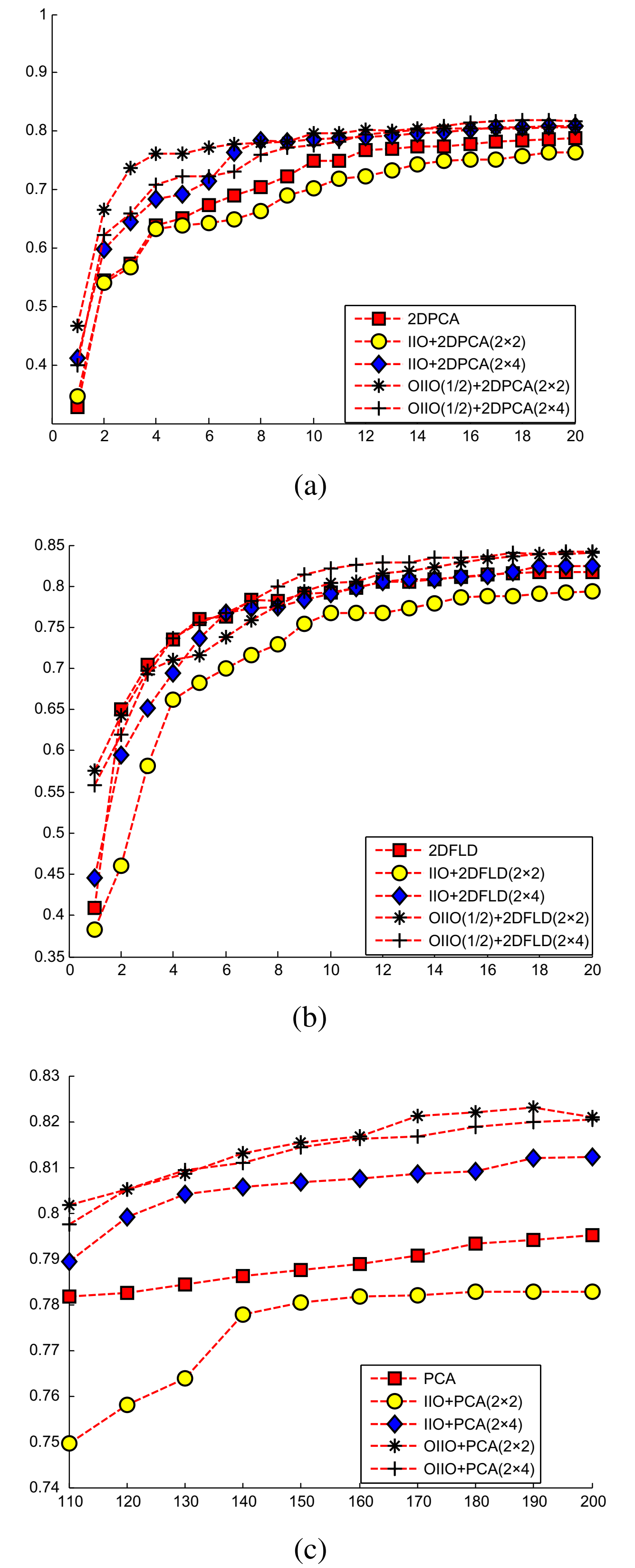

Fig. 6. Face recognition results on the AR database obtained by different linear feature extraction procedures combined with or without improved interest operator 1. (a) Classification right rate associated with 2DPCA, (b) classification right rate associated with 2DFLD and (c) classification right rate associated with PCA.

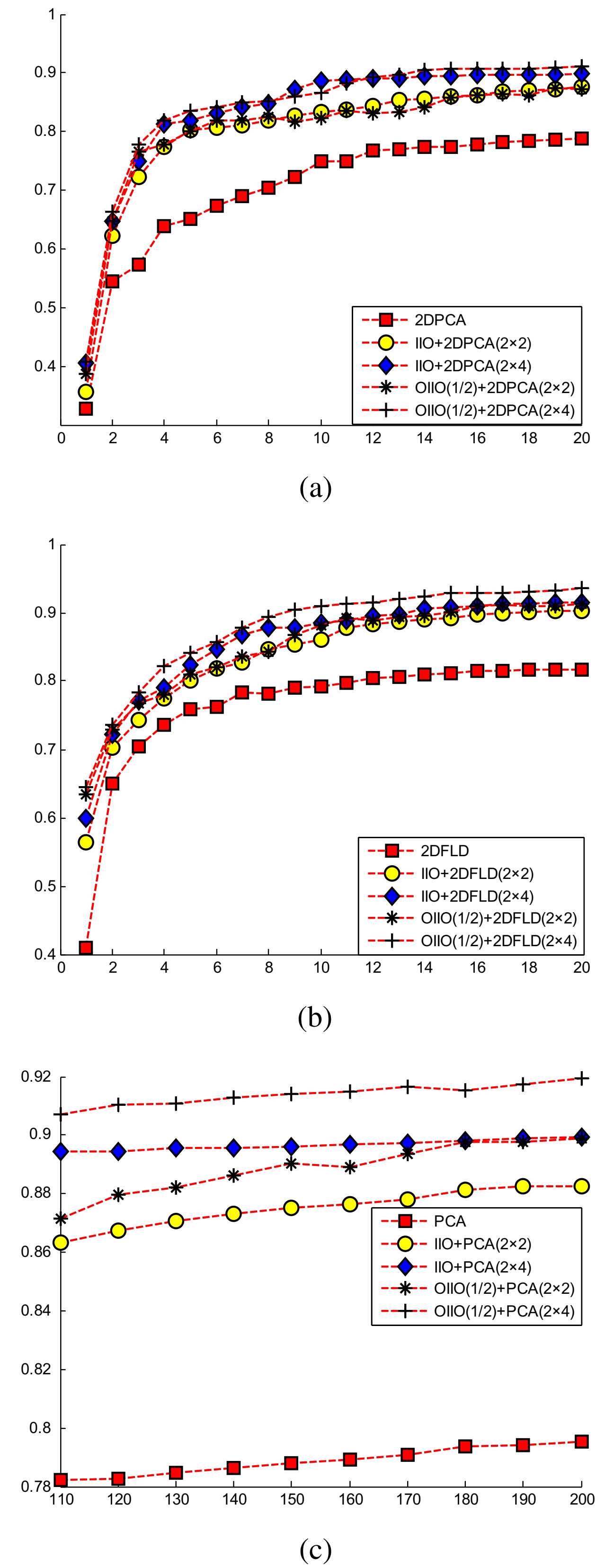

Fig. 7. Face recognition results on the AR database obtained by different linear feature extraction procedures combined with or without improved interest operator 2. (a): classification right rate associated with 2DPCA. (b): classification right rate associated with 2DFLD. (c): classification right rate associated with PCA.

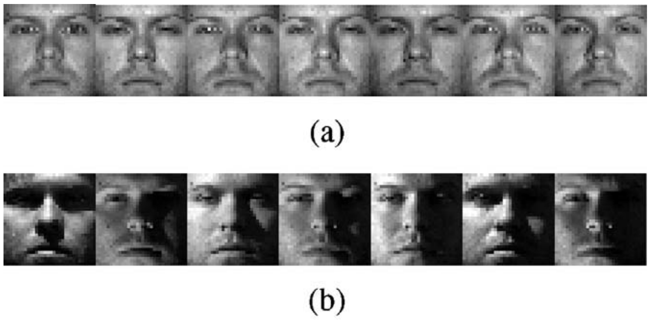

Fig. 8. Some face images of a same face. These images are obtained under different illumination conditions. (a) Face images obtained in the cases where the azimuth angle and the elevation angle of the light source with respective to the camera axis are small. (b) Face images obtained in the cases where the azimuth angle and the elevation angle of the light source with respective to the camera axis are quite large.

kaÂcs (1998) and Wang et al. (1998) are three typical examples of the second class. In TakaÂcs (1998), the binary coding result of Sobel edge detection operator was used as face edge feature. In Gao and Leung (2002), the line edge map approach detected the edge feature and then classified faces using the edge feature. It was assumed that image edge detection using gradient operators was almost not influenced by varying lighting condition (Gao & Leung, 2002); however, the approaches in Gao and Leung (2002), TakaÂcs (1998) and Wang et al. (1998) are all not able to obtain truly invariant facial features with respect to lighting condition. This is because the pixel intensity value varies with the lighting condition and consequently the gradient value seems to be also variable with respect to the lighting condition.

The interest operator appears to be also helpful for indicating salient image edge information in different directions as shown in Fig. 4. Actually, an interest operator obtains 'average' directional edge of an image block since it sums gradient information in a certain direction. Improved interest operators have the following advantage: by improving the conventional interest operator, improved operators enable the obtained 'average' directional edge information of a face image block to be less variable with respect to the lighting condition. This is very beneficial to face recognition. In addition, since the average relative variation of the pixel intensity appears to in some extent be robust to facial expression and pose, improved interest operators may also produce more stable face feature than the conventional interest operator under the conditions of varying facial expression or pose.

5. Experimental result

In this section we compare our approach and the conventional interest operator using the AR and YaleB face databases. We evaluate the similarity between the feature extraction results of two face images by using

$$s(x,y) = \frac{x^T y}{||x|| \cdot ||y||}, \tag{17}$$

where x, y stand for two vectors respectively corresponding to the feature extraction results of the two face images. After the similarities between a testing sample and each of all training samples are computed, we select out the training sample that has the maximum similarity to the testing sample and classify the testing sample into the class that the selected training sample belongs to.

5.1. Experiments on the AR face database

The AR face database includes more than 4000 face images showing faces with different facial expressions, in varying lighting

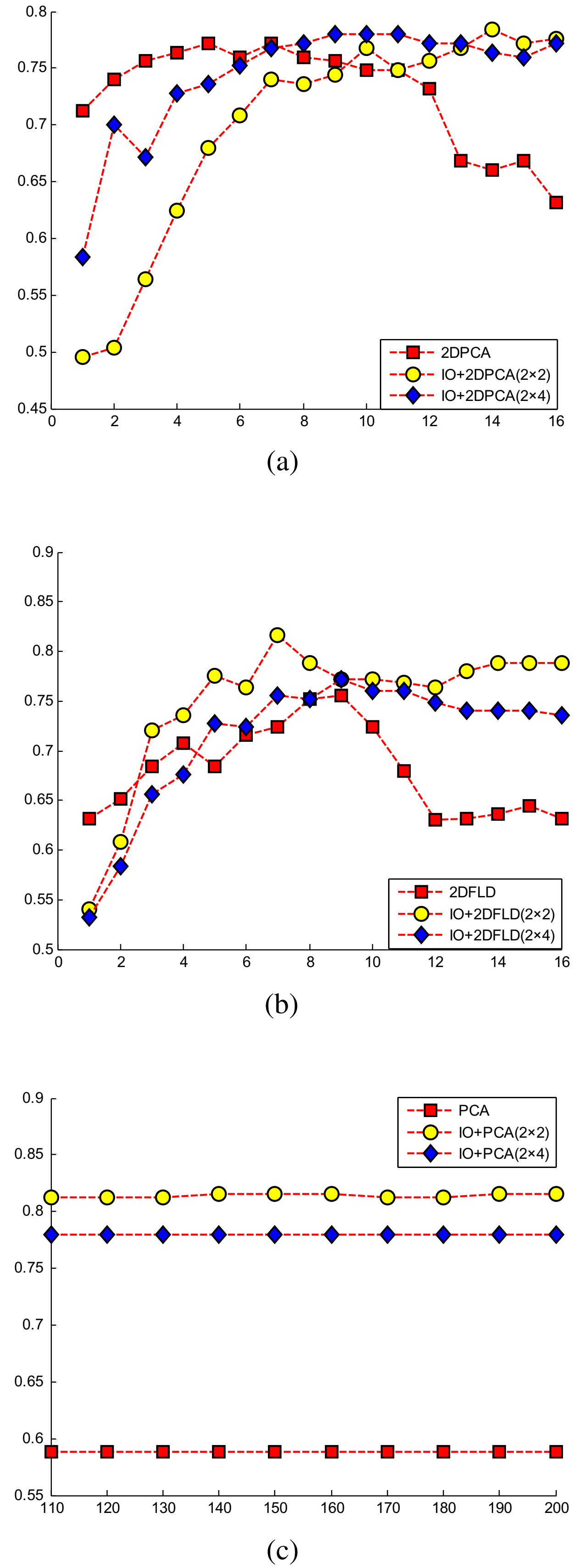

Fig. 9. Face recognition results on the YaleB database obtained by different linear feature extraction procedures combined with or without the conventional interest operator. (a): classification right rate associated with 2DPCA. (b): classification right rate associated with 2DFLD. (c): classification right rate associated with PCA.

conditions and occluded in several ways (Yang et al., 2004)[1]. Each subject have 26 face images. For each subject, the filenames of the 26 images contain the numbers from 1 to 26, respectively. If the number contained in the filename is 1, we call the image the first image of the subject, and so on. We use the computer generates 13 random integers in the range of from 1 to 26. For every subject, we take the 13 images whose filenames contain the numbers from the random integer sequence as the training samples and consider the remaining samples as test samples. The generate random integer sequence is 2, 4, 7, 8, 10, 15, 16, 19, 21, 22, 24, 25, 26.

Fig. 5 shows face recognition results on the AR database obtained by different linear feature extraction procedures combined with or without the conventional interest operator. Note that hereafter by IO (Interest Operator) we denote the conventional interest operator. By IIO1 we denote improved interest operator 1 based on the non-overlapping partition scheme. By IIO2 we denote improved interest operator 2 based on the non-overlapping partition scheme. In addition, we use OIIO1 (Overlapped Improved Interest Operator 1) to represent improved interest operator 1 based on the overlapping partition scheme. We also use OIIO2 to represent improved interest operator 2 based on the overlapping partition scheme. If the interest operator is followed by a linear feature extraction procedure, we add some indicators to the denotation. For example, 'IO + 2DPCA' means that feature extraction is implemented by the conventional interest operator followed by 2DPCA. We use a bracket to show the size of each block or the overlapping region. For example, 'IO + 2DPCA(2×2)' means that the image is partitioned into a number of 2×2 non-overlapping image blocks; whereas 'OIIO(1/2) + 2DPCA(2×2)' means that the image is partitioned into a number of 2×2 overlapping image blocks and 1/2 regions of two neighboring blocks are overlapped each other.

According to Fig. 5, the combination of PCA and the conventional interest operator is not able to obtain a higher accuracy than PCA. The combination of 2DPCA and the conventional interest operator may produce a higher or lower accuracy than 2DPCA. So does the combination of 2DFLD and the conventional interest operator.

Table 1 shows experimental result comparison of our approach and other approaches on the AR face database. From Table 1 and Figs. 5–7, we can see that the combination of either of the two improved interest operators and 2DPCA or 2DFLD can produce a higher accuracy than 2DPCA or 2DFLD. The combination of an improved interest operator and 2DPCA or 2DFLD also performs better than the combination of the conventional interest operator and 2DPCA or 2DFLD. Fox example, the combination of the conventional interest operator and 2DPCA obtains the mean of recognition accuracy of 69.5% and the best accuracy of 79.0%. When OIIO1 is combined with 2DPCA, the mean of the accuracy and the best accuracy are 75.7% and 81.7%, respectively. For the combination of OIIO2 and 2DPCA, the mean of the accuracy and the highest accuracy are 82.2% and 91.9%, respectively. This means that compared to the combination of the conventional interest operator and 2DPCA, the combination of OIIO2 and 2DPCA improves the mean accuracy and the highest accuracy 12.7% and 12.9%, respectively.

5.2. Experiments on the YaleB face database

The images in the YaleB database[2] are obtained with varying illuminations and unfixed poses and there exists a wide rang of illumination cases. To focus on face recognition with varying illuminations, we select and use 45 face images with pose 00 of every person. We crop each of these images to obtain a 32×32 image

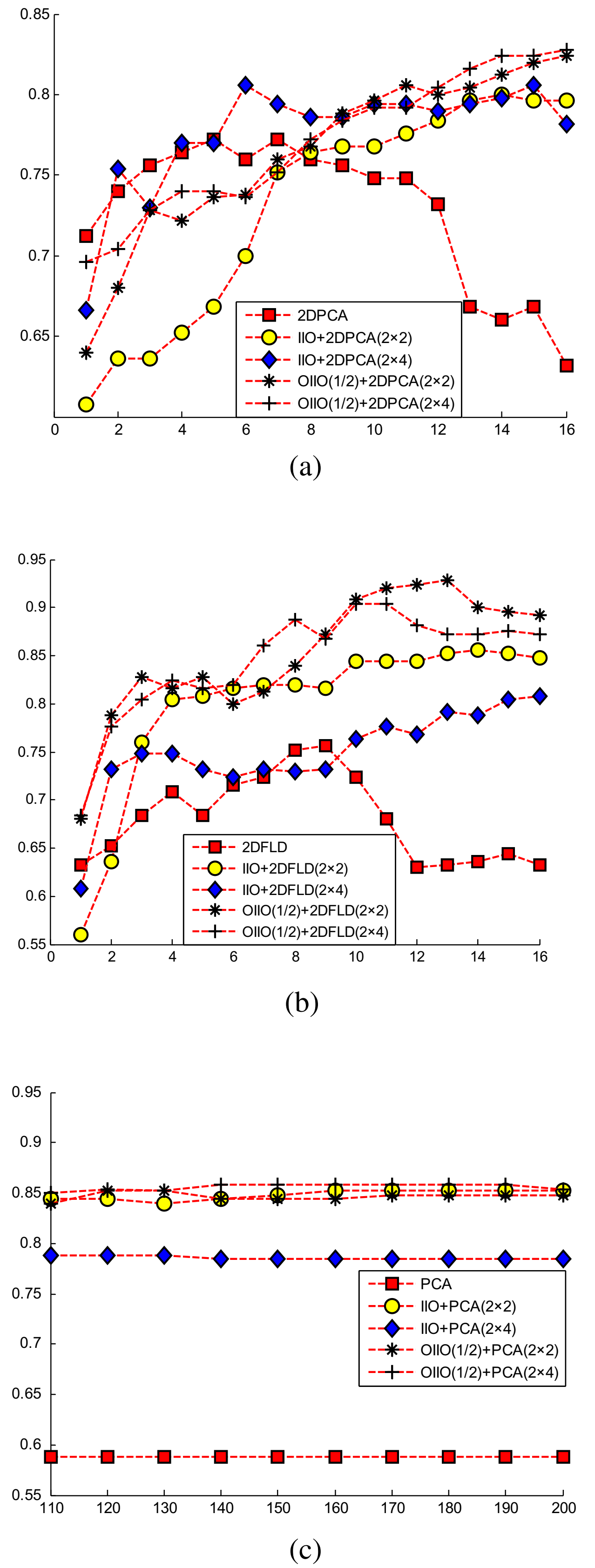

Fig. 10. Face recognition results on the YaleB database obtained by different linear feature extraction procedures combined with or without improved interest operator 1. (a): classification right rate associated with 2DPCA. (b): classification right rate associated with 2DFLD. (c): classification right rate associated with PCA.

[1] http://cobweb.ecn.purdue.edu/~aleix/aleix_face_DB.html; http://cobweb.ecn.purdue.edu/~aleix/ar.html.

[2] http://cvc.yale.edu/projects/yalefacesB/yalefacesB.html.

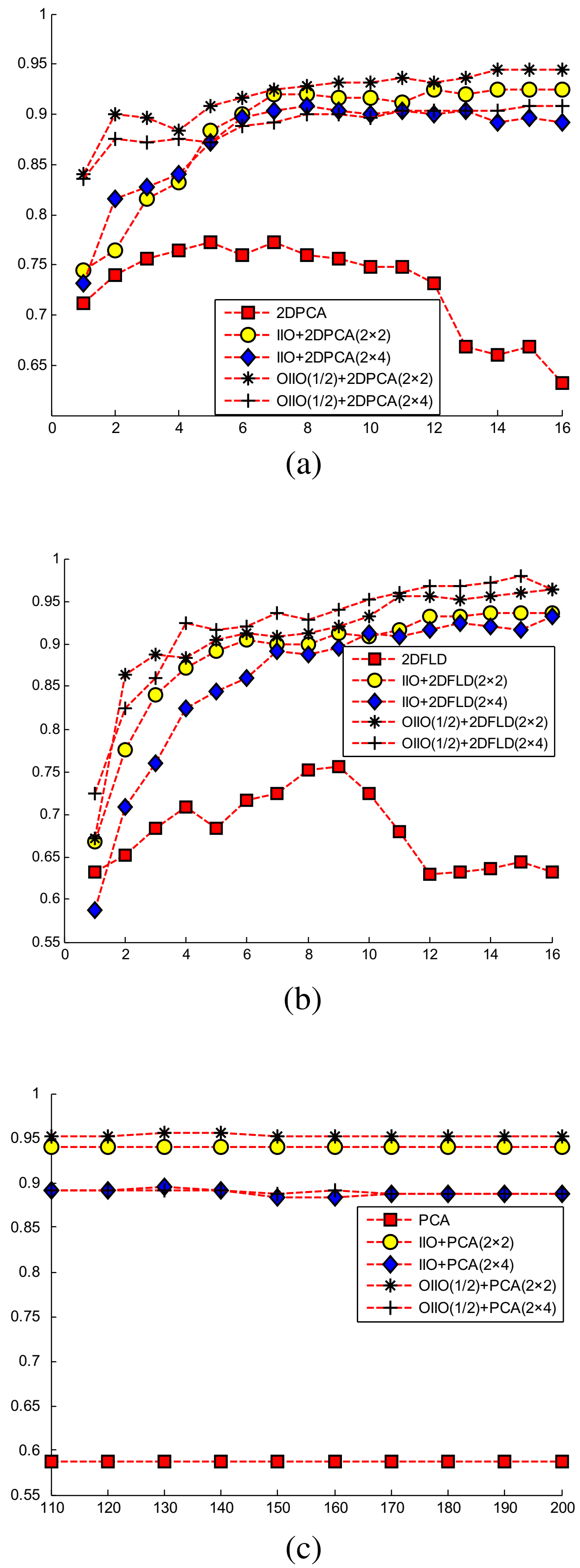

Fig. 11. Face recognition results on the YaleB database obtained by different linear feature extraction procedures combined with or without improved interest operator 2. (a): classification right rate associated with 2DPCA. (b): classification right rate associated with 2DFLD. (c): classification right rate associated with PCA.

Table 2
Experimental result comparison of our approach and other approaches on the YaleB face database.

	Best accuracy(%)	Mean of the accuracy(%)	Size of the block
2DPCA	77.2	74.5	
2DFLD	75.2	69.0	
PCA	58.8	58.8	
IO + 2DPCA	78.4	70.9	2 × 2
IO + 2DFLD	78.8	72.3	2 × 2
IO + PCA	81.6	79.7	2 × 2
OIIO1 + 2DPCA	82.8	75.5	2 × 4
OIIO1 + 2DFLD	92.8	84.1	2 × 2
OIIO1 + PCA	85.8	85.1	2 × 4
OIIO2 + 2DPCA	94.4	89.9	2 × 2
OIIO2 + 2DFLD	98.0	90.3	2 × 4
OIIO2 + PCA	95.6	92.1	2 × 2

(Xu, Yang, Jin, & Zheng, 2006). We test our approach using the obtained images. Some face images of a same face are shown in Fig. 8.

Fig. 9 shows face recognition results on the YaleB database obtained by different linear feature extraction procedures combined with or without the conventional interest operator. Fig. 10 shows face recognition results on the YaleB database obtained by different linear feature extraction procedures combined with or without improved interest operator 1. Fig. 11 shows face recognition results on the YaleB database obtained by different linear feature extraction procedures combined with or without improved interest operator 2. Table 2 shows experimental result comparison of our approach and other approaches on the YaleB face database. Table 2 and Figs. 9–11 show that the combination of improved interest operator 1 or 2 and a linear feature extraction procedure performs better than the combination of the conventional interest operator and the same linear feature extraction procedure. Fox example, the combination of the conventional interest operator and 2DFLD obtains the mean of recognition accuracy of 72.3% and the highest recognition accuracy of 78.8%. When OIIO1 is combined with 2DFLD, the mean of the accuracy and the highest accuracy are 84.1% and 92.8%, respectively. For the combination of OIIO2 and 2DFLD, the mean of the accuracy and the highest accuracy are 90.3% and 98.0%,, respectively. This means that compared to the combination of the conventional interest operator and 2DFLD, the combination of OIIO2 and 2DFLD improves the mean accuracy and the highest accuracy 18.0% and 19.2%, respectively.

5.3. More experimental analysis

In this subsection, we further investigate our approach by analyzing the similarity of different images of the same face for the AR face database. Analysis is performed for the first, second, seventh, eighth and eleventh face images of each subject. The used five images of one subject are shown in Fig. 12. When compared with image (a), images (b) has different expression, image (c) is obtained under different lighting condition, images (d) and (e) are two occluded face images.

Note that after the conventional interest operator or the proposed interest algorithm is applied to all the five images of a face, we can also evaluate the similarities between the resultant images

Fig. 12. Illustration of the five images of a face used for similarity analysis.

Table 3
Means of the similarities between the resultant images of (a) and those of (b), (c), (d), (e). Each row shows the means of the similarities between the resultant images associated with an interest operator of image (a) and images (b), (c), (d), (e). IIO1 and IIO2 respectively denote improved interest operators 1 and 2 applied to the non-overlapping partition scheme.

	Similarity of (b) and (a)	Similarity of (c) and (a)	Similarity of (d) and (a)	Similarity of (e) and (a)
IO	0.916	0.861	0.848	0.816
IIO1	0.946	0.941	0.914	0.868
OIIO1	0.950	0.950	0.920	0.877
IIO2	0.966	0.959	0.924	0.901
OIIO2	0.968	0.964	0.938	0.911

of image (a) and each of images (b), (c), (d), (e) by using $s_1(x_1, y_1) = \frac{x_1^T y_1}{\|x_1\| \times \|y_1\|}$, where x_1, y_1 represent the two one-dimensional vectors of the resultant images of the two original face images, respectively. Note that an interest operator produces five resultant images for each original image, so the corresponding one-dimensional vector used for similarity computation is obtained by treating the five resultant images of the original image as an integral image and by concatenating the rows or columns of the integral image.

For each subject, we respectively compute the similarities between the resultant images of image (a) and those of images (b), (c), (d), (e) produced by an interest operator. Then we calculate the means of the similarities based on all the subjects. The means obtained in the case where each image block is of the same size of 2×2 are shown in Table 3. In the overlapping block partition scheme, half of each block is overlapped by a neighboring block. The second to fifth columns of Table 3 respectively show the means of the similarities between the resultant images of image (a) and those of images (b), (c), (d), (e).

From Table 3, we can see that, when improved interest operators 1 and 2 are applied to non-overlapping image blocks, the obtained similarities between the resultant images are higher than the similarities of the resultant images obtained using the conventional interest operator. Moreover, OIIO1 and OIIO2 produce higher similarities respectively than IIO1 and IIO2. This implies that the combination of the improved interest operator and the overlapping block partition scheme is more helpful for obtaining high similarities than the combination of the improved interest operator and the non-overlapping partition scheme. Therefore, we can conclude that both the improved interest operator and the overlapping partition scheme are useful for resulting in higher similarities for the resultant images of image (a) and those of images (b), (c), (d), (e). This also means that our approach can effectively reduce the difference between different images of the same face, which is very beneficial to face recognition.

6. Conclusion

The new approach proposed in this paper differs from the feature extraction approach using the conventional interest operator in the following two aspects. The first aspect is that the proposed approach takes the relative rather than absolute variation of the pixel intensity as the feature of an image block. This allows the proposed approach to obtain robust block features that are less affected by varying imaging conditions such as varying lighting and facial expression. The second aspect is that the proposed approach adopts the overlapping block partition scheme. This enables the proposed approach to fully reflect the pixel intensity variation information and to produce more representative feature extraction results. As a result, the proposed approach can do better in face recognition than the conventional interest operator.

The analysis and experimental results illustrate the feasibility and the satisfactory performance of the proposed approach. Experimental results show that the use of the proposed approach can obtain more than 10 percent accuracy improvement.

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