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Integrate the original face image and its mirror image for face recognition

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ABSTRACT

The face almost always has an axis-symmetrical structure. However, as the face usually does not have an absolutely frontal pose when it is imaged, the majority of face images are not symmetrical images. These facts inspire us that the mirror image of the face image might be viewed as a representation of the face with a possible pose opposite to that of the original face image. In this paper we propose a scheme to produce the mirror image of the face and integrate the original face image and its mirror image for representation-based face recognition. This scheme is simple and computationally efficient. Almost all the representation-based classification methods can be improved by this scheme. The underlying rationales of the scheme are as follows: first, the use of the mirror image can somewhat overcome the misalignment problem of the face image in face recognition. Second, it is able to somewhat eliminate the side-effect of the variation of the pose and illumination of the original face image. The experiments show that the proposed scheme can greatly improve the accuracy of the representation-based classification methods. The proposed scheme might be also helpful for improving other face recognition methods.

1. Introduction

As we know, the main challenges of face recognition are that the face image might severely vary with the various poses, facial expression and illumination [1–3]. A face recognition method greatly suffers from these challenges. In order to address these challenges, people have made many efforts. For example, Jian et al. proposed the illumination compensation method for face recognition [4]. Sharma et al. proposed pose invariant virtual classifiers for face recognition [5]. We also note that if the available training samples of a face can sufficiently show possible variations of the pose, facial expression and illumination, it will be possible to obtain a high accuracy. Unfortunately, in real-world applications a face usually has only a very small number of training samples, which cannot convey many variations of the face [6–10]. In order to overcome the problem that the training samples of a face do not convey sufficient variations of the face, previous literatures have proposed some approaches to generate new (i.e. virtual or synthesized) face images and to enlarge the size of the set of the training samples.

It is known that both the facial structure and the facial expression are symmetrical [11]. Previous literatures have successfully exploited the symmetrical structure of the face for face detection [11–14]. However, it should be pointed out that in real-world face recognition applications, a large number of face images are not symmetrical images due to non-frontal and non-neutral pose [15]. Xu et al. proposed an approach to generate "symmetrical" face images and exploited both the original and "symmetrical" face images to recognize the subject [15]. As the "symmetrical" face image is generated with the assumption that the facial structure is symmetrical, it is an axis-symmetrical image. However, as shown later, the "symmetrical" face images obtained in [15] is not a natural face image and even appear to be strange.

A real-world face recognition application also often suffers from the misalignment problem of the face image. This problem certainly makes the face image not symmetrical and is advantageous for correctly recognizing the face. Fig. 3 presented later shows an example of misalignment of the face image.

It should be pointed out that though previous literatures have made many efforts in making virtual or synthesized face images which reflect the variation of the face as much as possible, almost

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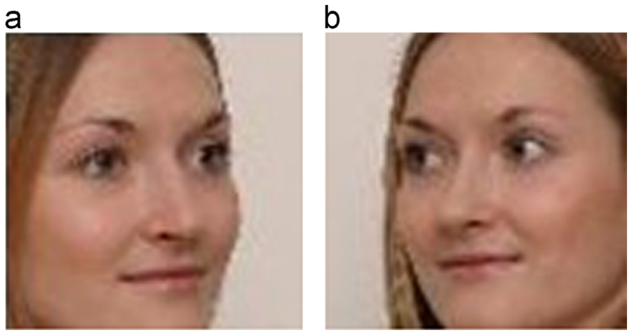

Fig. 1. An original face image with a left tilt pose (a) and another original face image right tilt pose (b) of a same subject. It is clear that these two face images have great difference in terms of the distance metric.

no literature generated virtual or synthesized face images by exploiting the special nature of the face i.e. the symmetry of the structure. This motivates us to exploit the symmetrical structure of the face to improve previous face recognition methods.

In this paper, we propose a novel scheme to improve the face recognition method. The proposed scheme first generates the mirror image of the original face image and then applies a representation-based classification (RBC) method to both the original face image and its mirror image to perform face recognition. We also refer to the mirror image of the original face image as face mirror image. The rationales of the proposed scheme are as follows: first, the face mirror image reflects some possible change in pose and illumination of the original face image. For example, if two original face images of a same subject have a left tilt pose and right tilt pose, then the difference between them will be great in terms of the distance metric. If these two face images from the same face are used as training and test samples, then the test sample will be hard to be correctly classified. The example shown in Fig. 1 clearly illustrates this. As a consequence, the face recognition method using only the original face images will be very hard to obtain satisfactory accuracy. However, the difference between either of the two original face images and the mirror image of the other original face image might be very little in terms of the distance metric. As a result, the use of the face mirror image will be very useful for correctly classifying the test sample. For detailed demonstration, refer to Section 5. Second, the face mirror image is very useful to overcome the possible misalignment problem of the original face image (for detail refer to Section 5). The results of various experiments on face recognition also show that the proposed scheme is quite feasible and can improve the state-of-the-art representation-based classification methods.

This paper has the following main contributions. First, it proposes the scheme to integrate the original face images and their mirror images for representation-based face recognition. It also describes the rationale of the proposed scheme. Second, it shows that a number of representation-based classification methods can be improved by using the proposed scheme.

The remainder of the paper is organized as follows. Section 2 presents related works. Section 3 presents representation based classification methods. Section 4 describes our proposed scheme. Section 5 describes the rationales of the proposed scheme. Section 6 shows the experimental results and Section 7 offers the conclusion.

2. Related works

Because our proposed scheme is based on representation-based classification (RBC) methods and the generated virtual face images, this section mainly reviews the literatures of generating virtual or synthesized face images and those literatures on RBC methods. A number of previous works focus on generating virtual or synthesized face images and on enlarging the size of the set of the training samples. For example, Tang et al. [16] obtained "virtual" facial expression by exploiting the prototype faces and optic flow. Jung et al. [17] obtained new samples of the face by using the noise. Thian et al. [18] used simple geometric transformations to make virtual samples. Ryu et al. [19] exploited the distribution of the training samples to produce virtual training samples of the face. Sharma et al. [5] extended training samples by generating multiple virtual views of a person under different poses and illumination from a single face image. Beymer et al. [6] and Vetter et al. [7] also addressed this issue by generating new samples with virtual views.

Among a variety of face recognition methods, the representation-based classification (RBC) method can achieve a very high accuracy and has received much attention [20–23]. The conventional RBC method is also referred to as sparse representation classification (SRC) method [20–22]. RBC including SRC assumes that the test sample can be well represented by a linear combination of all the training samples. SRC obtains its solution using the constraint of the ℓ_1 norm minimization. In other words, SRC achieves its solution with the sparsity constraint which assumes that a number of the coefficients of the linear combination are equal or close to zeroes. We also say that SRC uses a sparse linear combination of all the training samples to represent the test sample.

Besides SRC, RBC can be also implemented by using the constraint of the ℓ_2 norm minimization [24–26]. The corresponding method can be referred to as RBC with the ℓ_2 norm minimization constraint. It seems that the algorithm of RBC with the ℓ_2 norm minimization constraint is simpler and easier to implement than that of SRC. There are two kinds of RBC with the ℓ_2 norm minimization constraint. The first kind exploits the training samples from all the classes to represent the test sample and uses the representation result to perform classification [24–26]. The sparsity constraint is imposed on only a few methods of this kind. For example, the methods proposed by Shi et al. [23] and by Zhang et al. [25] have no sparsity constraint. In other words, these two methods do not require that the coefficients of the linear combination to represent the test sample are equal or close to zeroes. On the other hand, the sparsity constraint is imposed on the method proposed in [26] in a special way. The second kind exploits the training samples from each class to represent the test sample and the classification is also performed in terms of the representation result [27,28]. The sparsity constraint is also not imposed on this kind of method. Specially, this kind of method usually assumes that the test sample can be respectively approximately represented by a linear combination of the training samples of every class and no any constraint sparsity is imposed on the coefficients of the linear combination. A typical example of this kind of method is linear regression classification (LRC) [27]. The sparse representation has also been used to other problems such as sparse graph based image annotation [29], super-resolution reconstruction [30], image alignment [31] and image de-noising [32]. The sparsity has also been used to modify discriminant analysis [33,34] and locality preserving projection [35,36]. The sparse graph is also used in video semantic annotation [36] and representative image selection [37,38]. For recent advances and more applications of RBC, refer to literatures [39–41].

3. Representation based classification (RBC)

In this section, we introduce representation based classification (RBC) briefly. Because LRC has a distinct characteristic, we describe it in Section 3.1 and present other RBCs in Section 3.2. We assume that there are c classes and each class has n training samples in the form of column vectors. Let $x_1, \ldots, x_N$ be all the N training samples in the form of column vectors ($N = cn$). Column vector $x_{(i-1)n+k}$

($k=1,\ldots,n$) stands for the k-th training sample of the i-th subject, $i=1, 2, \ldots, c$. Let column vector z stand for the test sample.

3.1. LRC [27]

In this subsection we present the algorithm of LRC as follows. LRC establishes an equation for each class. The equation of the i-th class is

$$z=X_iA_i \tag{1}$$

where $A_i=[a_1^i \ldots a_n^i]$, $X_i=[x_{(i-1)*n+1}\ldots x_{i*n}]$. The solution of Eq. (1) is obtained using

$$\hat{A}_i=(X_i^TX_i)^{-1}X_i^Tz \tag{2}$$

The deviation between the i-th class and the test sample is defined as $d_i=\|z-X_i\hat{A}_i\|$. If $k=\arg\min_i d_i$, then the test sample is assigned to the k-th class.

3.2. Brief introduction to other RBCs

For the representation based classification methods, all the methods except for LRC first exploit a linear combination of all the training samples to represent the test sample.

RBC with the ℓ_2 norm minimization constraint can be briefly described as follows. We first take collaborative representation classification (CRC) as an example to show the basic characteristics of this kind of method. CRC assumes that Eq. (3) is approximately satisfied

$$z=XB \tag{3}$$

where $B=[b_1\ldots b_N]^T$, $X=[x_1\ldots x_N]$. The solution of Eq. (3) is usually obtained using

$$\hat{B}=(X^TX+\mu I)^{-1}X^Tz \tag{4}$$

μ is a small positive constant and I is the identity matrix. Let $\hat{B}=[\hat{b_1}\ldots\hat{b_N}]^T$. Of course, if X^TX is not singular, the solution of Eq. (3) can be also obtained using

$$\hat{B}=(X^TX)^{-1}X^Tz \tag{5}$$

CRC calculates the residual of the test sample with respect to the i-th class using $r_i=\|z-X_i\hat{B}_i\|$ where $X_i=[x_{(i-1)*n+1}\ldots x_{i*n}]$ and $\hat{B}_i=[\hat{b}_{(i-1)*n+1}\ldots\hat{b}_{i*n}]^T$. If $k=\arg\min_i r_i$, then CRC assigns the test sample to the k-th class.

The main difference between CRC and the other RBCs with the ℓ_2 norm minimization constraint is that other RBCs might have extra constraints or steps. For example, the improvement to the nearest neighbor classifier (INNC) [42] has the same equation and solution scheme as CRC but uses a simpler classifier. The two-phase sparse representation (TPSR) method [24] has the same first step as CRC but exploits an extra step to obtain a sparse linear combination of all the training samples to represent the test sample.

SRC, i.e. RBC with the ℓ_1 norm minimization constraint can be briefly described as follows. SRC attempts to solve the following problem:

$$\min_B \|B\|_1, \quad \text{s.t.}\|z-XB\|_2\le\varepsilon \tag{6}$$

where $\varepsilon>0$ is a constant. SRC has no closed solution and should be iteratively solved. The original SRC algorithm is very computationally inefficient and recently some efficient algorithms for SRC have been proposed [43,44].

4. The proposed scheme

The main motivation of our proposed scheme is to use a simple way to obtain more training samples and to improve the face recognition accuracy. Though the used mirror image is simply generated from the original face image, it also appears to be a natural image and properly reflects possible variation of the original face image in pose and illumination. Moreover, the mirror image is also sufficiently different from the original face image in terms of the distance metric, so the use of the mirror image does enable the face recognition method to exploit more available information of the face. In this section we describe the proposed scheme in detail. The proposed scheme works as follows. It first generates the mirror image of each original face image for training. It then exploits both the original face image of a face for training and the corresponding mirror image as training samples of this face. As a result, a face has $2n$ training samples in total. For the i-th face, we use $y^0_{(i-1)n+k}$ ($k=1,\ldots,n$) to denote the mirror image of original face image $x^0_{(i-1)n+k}$, respectively. $x^0_{(i-1)n+k}$ represents the original face image matrix corresponding to column vector $x_{(i-1)n+k}$. The algorithm of the proposed scheme can be presented as follows:

Step 1: Suppose that the original face image matrix has P rows and Q columns. The mirror image of an original face image has the same size. For the i-th face, mirror image $y^0_{(i-1)n+k}(k=1,\ldots,n)$ is generated using $y^0_{(i-1)n+k}(p,q)=x^0_{(i-1)n+k}(p,Q-q+1)$, $p=1, \ldots, P$, $q=1, \ldots, Q$. $x^0_{(i-1)n+k}(p,q)$ and $y^0_{(i-1)n+k}(p,q)$ denote the pixels located in the p-th row and q-th column of $x^0_{(i-1)n+k}$ and $y^0_{(i-1)n+k}$, respectively. $y^0_{(i-1)n+k}$ is then converted into a column vector and is denoted by $y_{(i-1)n+k}$. As all $x_{(i-1)n+k}$ and $y_{(i-1)n+k}$ act as training samples, we say that there are $2cn$ training samples in total.

Step 2: For the i-th face $(i=1,\ldots,c)$, let $X_i=[x_{(i-1)*n+1}\ldots x_{i*n}\ y_{(i-1)n+1}\ldots y_{i*n}]$. Actually, $X_1,\ldots,X_c$ are respectively the matrices consisting of all training samples including the original face images and mirror images of the first to the i-th faces. $x_{(i-1)*n+1}\ldots x_{i*n}$ and $y_{(i-1)*n+1}\ldots y_{i*n}$ are all column vectors. c stands for the number of the faces i.e. number of the subjects. Then X is defined as $X=[X_1\ldots X_c]$. A RBC method (LRC or an ordinary RBC method) is applied to each test sample and corresponding training samples. For an ordinary RBC method, the equation on test sample z is expressed as $z=XB$ and the solution is denoted by $\hat{B}$. If the applied method is LRC, then test sample z has c equations and the i-th equation is expressed as $z=X_iA_i$. Let $\hat{A_i}$ denote the solution of $z=X_iA_i$.

Step 3: For LRC, after solutions $\hat{A_1},\ldots,\hat{A_c}$ are obtained, the deviation between the test sample and the i-th subject is calculated using $d_i=\|z-X_i\hat{A}_i\|$. If $k=\arg\min_i d_i$, then LRC assigns the test sample to the k-th class. For other RBC methods, solution $\hat{B}$ is a vector and has $2cn$ entries. It is clear that each entry of $\hat{B}$ is associated with one column of X (i.e. one training sample). We refer to an entry of $\hat{B}$ as coefficient of the corresponding training sample. Let $\hat{B}_i$ be the vector consisting of $2n$ entries of $\hat{B}$ i.e. the coefficients of $x_{(i-1)*n+1},\ldots,x_{i*n}$, $y_{(i-1)*n+1},\ldots,y_{i*n}$. In other words, $\hat{B}_i$ is associated with the i-th subject. The residual of the test sample with respect to the i-th class is calculated using $r_i=\|z-X_i\hat{B}_i\|$. If $j=\arg\min_i r_i$, then test sample z is assigned to the j-th subject.

5. Rationales of the proposed scheme

5.1. Intuitive rationales of the proposed scheme

The proposed scheme has the following rationales: first, it is able to reduce the side-effect of the variation of the pose and

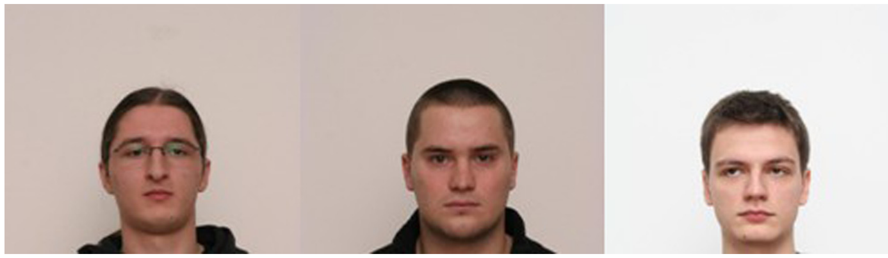

Fig. 2. Three photos with a homogeneous background.

Fig. 3. Test samples and training samples cropped from the photos shown in Fig. 2 as well as the mirror images of the training samples. The first and second rows show the test samples and training samples, respectively. The third row shows the mirror images of the training samples. The images in the same column are generated from a same face.

illumination of the original face image. Second, it can somewhat overcome the misalignment problem of the face image in face recognition. These rationales will be demonstrated in detail below.

We first show an example in which the proposed scheme can somewhat overcome the misalignment problem of the face image. Fig. 2 shows photos of three faces with a homogeneous background from the SCface database [45,46]. Fig. 3 shows test samples and training samples cropped from the photos shown in Fig. 2 as well as the mirror images of the training samples. They have the same size and are cropped from the same original photos. For the test and training samples in the same column, the face is the same but the test sample is a shift of the training sample. This means that there exists the misalignment problem of the face. We see from Table 1 that the Euclidean distance between the original test and training samples of the same subject, referred to as original distance of the same subject, is relatively larger. However, as also shown in Table 1, the Euclidean distance between the test sample and the mirror image of the training sample of the same subject, referred to as mirror distance of the same subject, is smaller. For two face images x^0 and y^0, we first convert them into column vectors x and y and calculate their Euclidean distance using $\sqrt{(x-y)^T(x-y)}$. We also see from Fig. 3 that for the same face the mirror image looks more similar with the test sample and will have a smaller distance from the test sample in comparison with the original training sample. This clearly illustrates that the use of the mirror image of the original face image is helpful for a "distance" based classifier to correctly classify the test sample and is able to reduce the side-effect of the mis-alignment problem of the original face image.

Table 1
The original and mirror distances of the samples shown in Fig. 3. Each sample has the size of 1400×1200.

No. of the subject	1	2	3
Original distance ($\times 10^5$)	1.97	2.01	2.23
Mirror distance ($\times 10^5$)	1.91	1.95	1.95

The following example shows that the proposed scheme can somewhat overcome the side-effect of the variation of the pose of

Fig. 4. Six test samples and six training samples from the SCface database as well as the mirror images of these training samples. The first and second rows show six test samples and six training samples, respectively. The third row shows the mirror images of the six training samples shown in the second row. The images in the same column are generated from a same face.

Table 2
The original and mirror distances of the samples shown in Fig. 4. Each sample has the size of 75×75.

No. of the subject	1	2	3	4	5	6
Original distance ($\times 10^3$)	9.94	8.33	8.72	8.61	9.90	8.82
Mirror distance ($\times 10^3$)	4.05	6.62	3.57	4.08	4.47	4.01

the original face image. Fig. 4 shows six test samples and six training samples from the SCface database [45,46] as well as the mirror images of these training samples. They have the same size but have different poses. Table 2 shows the original and mirror distances of the same subject. We see that for the same face the mirror distance is greatly smaller than the original distance. This implies that the simultaneous use of both the original face image and the mirror image will enable us to more accurately classify the face image.

The following example shows that the proposed scheme can somewhat overcome the variation of the illumination of the original face image. Fig. 5 shows several test samples and training samples of the same face from the Yale B database shown in Section 6.3. They have the same size but different illuminations. For the test sample, the right face has stronger illumination than the left face. For the training sample, the right face has weaker illumination than the left face. Table 3 shows the original and mirror distances on the samples shown in Fig. 5. The mirror distance is also much smaller than the original distance. This again implies that the use of the mirror image is beneficial for correctly recognizing the face.

5.2. More analyses of the proposed scheme

In this section, we will give more interpretation of the proposed scheme. As we know, RBC exploits the deviation or residual of each class to classify the test sample. RBC assigns the test sample to the class with the minimum deviation or residual. The deviation and residual indeed somewhat reflect the ability, to well represent the test sample, of the training samples of a class. The smaller the deviation or residual is, the greater the ability to well represent the test sample the corresponding class has.

Fig. 6 shows the deviations between a test sample and all the classes of the ORL face database. The deviations obtained using both LRC and the improvement to LRC (i.e. the integration of our proposed scheme and LRC) are shown in Fig. 6. This test sample is from the fifth class. From Fig. 6, we see that LRC will lead to erroneous classification of the test sample, since the corresponding deviation between the test sample and the fifth class is not the smallest. However, the improvement to LRC will obtain the correct classification result, because the corresponding deviation between the test sample and the fifth class is the smallest. Fig. 6 also implies that the improvement to LRC has stronger ability to represent the test sample than LRC.

Fig. 7 shows the deviations between a test sample and all the classes of the FERET face database. This test sample is from the nineteenth class. From Fig. 7, we see that LRC will lead to erroneous classification for this test sample, but the improvement to LRC will obtain the correct classification result. Shan et al. [8] also exploited the mirror image of the face image in recognizing the face, but the performance of his method is associated with the size of the blocks generated from the original face image.

The rationale of the proposed scheme can also be presented from the viewpoint of numerical analysis. For simplicity of presentation, we just take LRC and the improvement to LRC as an example. Suppose that test sample is from the i-th class. As the improvement to LRC has more available training samples than LRC, it is easy to know that the deviation between the i-th class and the test sample obtained using the improvement to LRC is usually smaller than that obtained using LRC.

5.3. Comparison of our scheme with the one proposed in [15]

In this subsection, we show the difference between our scheme and the scheme proposed in [15]. The scheme proposed in [15] is able to obtain a virtual axis-symmetrical face image. As shown in [15], these virtual face images can somewhat reflect possible variation in pose and scale of the face. However, the "symmetrical" face images obtained in [15] have the following shortcoming: they are not natural face images and even appear to be strange. Figs. 8 and 9 show some reasonable and unreasonable "symmetrical" face images obtained in [15]. From Fig. 9, we see that unreasonable "symmetrical" face images do appear not to be natural face images.

Fig. 5. Six test samples and six training samples from the Yale B database as well as the mirror images of these training samples. The first and second rows show six test samples and six training samples, respectively. The third row shows the mirror images of the six training samples shown in the second row. The images in the same column are generated from a same face.

Table 3
The original and mirror distances on the samples shown in Fig. 5.

No. of the column	1	2	3	4	5	6
Original distance ($\times 10^4$)	2.47	2.16	3.23	2.30	2.07	1.36
Mirror distance ($\times 10^4$)	2.34	2.01	3.10	2.15	1.95	1.21

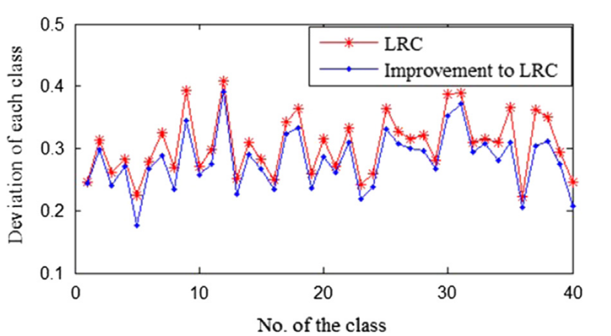

Fig. 6. The deviations between a test sample and all the classes of the ORL face database. The deviations are obtained by using LRC and the improvement to LRC. The test sample is from the fifth class.

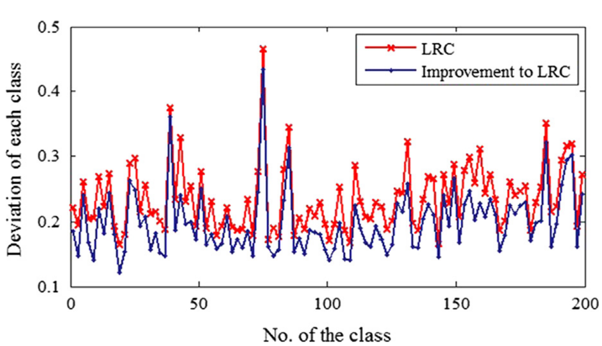

Fig. 7. The deviations between a test sample and all the classes of the FERET face database. The deviations are obtained by using LRC and the improvement to LRC. The test sample is from the nineteenth class.

For example, some unreasonable "symmetrical" face images have a very big or small nose, which not only makes the "symmetrical" face image far from the original true face image but also looks ugly.

Differing from the virtual face image obtained using the scheme proposed in [15], the virtual face image i.e. mirror image of the original face image generated from our scheme always looks like a true face image. Another difference between the scheme proposed in [15] and our scheme is as follows. The "symmetrical" face images obtained in [15] indeed contains much redundant information, because it is a strictly axis-symmetrical face image, the left face of which is the mirror image of the right face. In other words, one half of the pixels in the "symmetrical" face image seem to be redundant. However, the virtual face image generated from our scheme is not an axis-symmetrical face image and does not have the same kind of redundant information as the "symmetrical" face images obtained in [15]. In addition, because our scheme generates only one virtual face image for an original face image and the scheme proposed in [15] obtains two virtual face images for an original face image, our scheme is simpler and easier to implement.

6. Experimental results

6.1. Experiments on the FERET face database

We first used a subset of the FERET face database to test our method. This subset consists of 1400 images from 200 subjects each providing seven images [47]. This subset was composed of images whose names are marked with two-character strings: 'ba', 'bj', 'bk', 'be', 'bf', 'bd', and 'bg'. We resized each image to a 40×40 image using the down-sampling algorithm. We took the first 1, 2, 3 and 4 face images of each subject as original training samples and treated the remaining face images as test samples. Table 4 shows the rates of classification errors of different methods. We see that our proposed scheme can improve LRC, CRC, SRC, INNC and coarse to fine k nearest neighbor classifier (CFKNNC) [48]. Hereafter, the integrations of our proposed scheme and LRC, CRC, SRC, INNC as well as KNNC are referred to as the improvements to

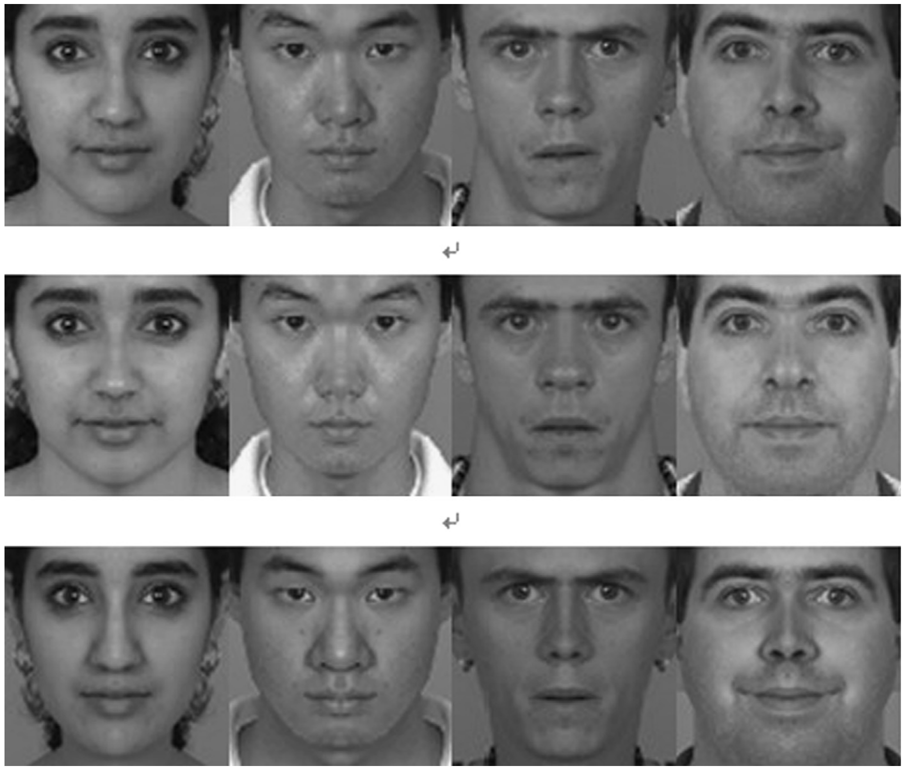

Fig. 8. Some original face images from the FERET face database and the corresponding "symmetrical" face images. The first row shows the original face images. The second and third rows respectively show the first and second symmetrical face images, of the original face images, obtained using the scheme proposed in [15]. Because these "symmetrical" face images appear to be natural face images, we refer to them as reasonable "symmetrical" face images.

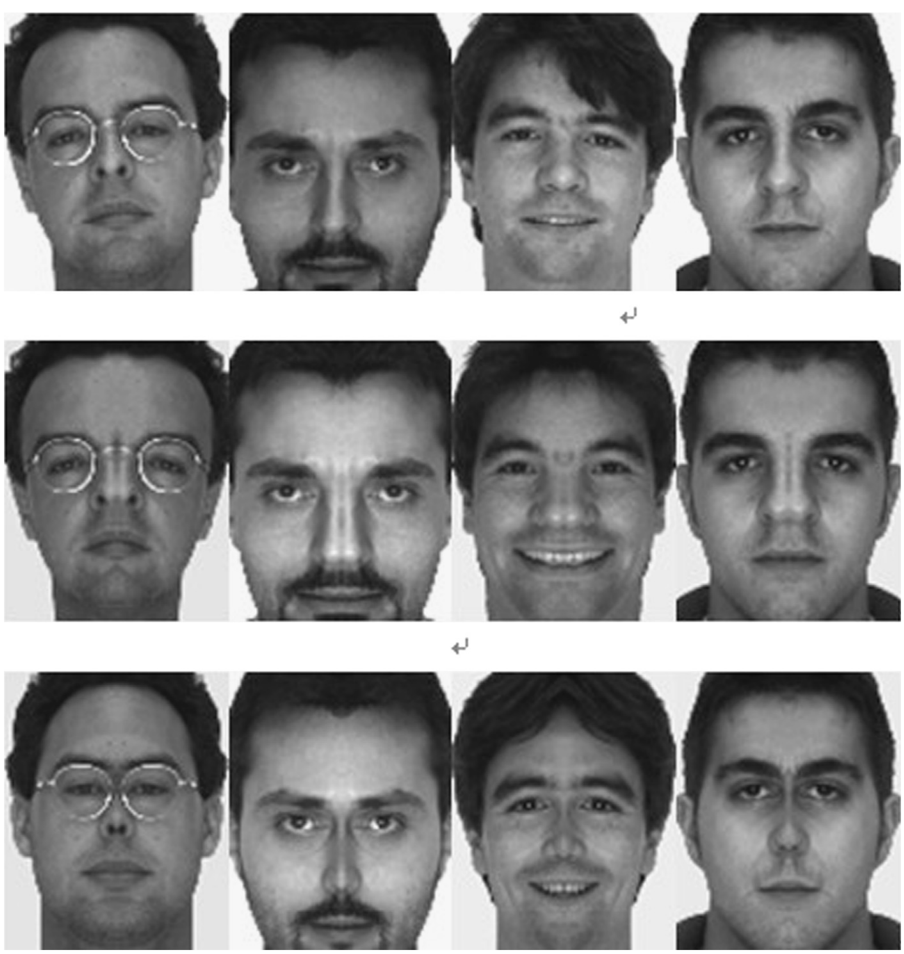

Fig. 9. Some original training samples from the AR face database and the corresponding symmetrical face images. The first row shows the original face images. The second and third rows respectively show the first and second symmetrical face images, of the original face images, obtained using the scheme proposed in [15]. Because these "symmetrical" face images appear not to be natural face images, we refer to them as unreasonable "symmetrical" face images.

Table 4
The rates of classification errors (%) of different methods on the FERET database.

Number of the training samples of each subject	4	3	2	1
LRC	21.5	40.13	35.90	55.08
Improvement to LRC	14.17	22.13	22.40	50.83
INNC	42.67	49.50	41.70	56.50
Improvement to INNC	35.50	35.75	33.50	54.08
CRC	44.67	55.63	41.60	55.67
Improvement to CRC	36.50	36.88	34.50	53.25
SRC	23.33	40.00	35.20	49.75
Improvement to SRC	21.00	39.75	34.70	49.00
CFKNNC	38.50	45.12	36.70	52.17
Improvement to CFKNNC	25.50	29.00	27.70	51.17

Table 5
The rates of classification errors (%) of different methods on the ORL database.

Number of the training samples of each subject	4	3	2	1
LRC	13.75	18.57	20.62	32.50
Improvement to LRC	12.08	12.14	17.81	28.89
INNC	12.50	17.86	18.44	28.33
Improvement to INNC	14.17	14.64	16.56	28.06
CRC	11.50	13.93	16.56	31.94
Improvement to CRC	13.33	12.14	14.69	28.89
SRC	10.00	14.29	15.00	27.50
Improvement to SRC	8.33	12.14	14.06	26.67
CFKNNC	14.58	19.29	17.81	26.39
Improvement to CFKNNC	12.50	14.29	15.00	26.67

LRC, CRC, SRC, INNC as well as KNNC, respectively. When each subject provided two training samples, the rates of classification errors of LRC, CRC, INNC and CFKNNC are 35.9%, 41.6%, 41.7% and 36.70%, respectively. However, the rates of classification errors of the improvements to LRC, CRC, INNC and CFKNNC are 22.4%, 34.5%, 33.5%, and 27.70%, respectively. When CFKNNC and improvement to CFKNNC were implemented, we set parameter n and K to $n = N/4$ and $K=1$. N stands for the number of all the original training samples. $K=1$ means that the nearest neighbor classification is indeed performed.

6.2. Experiments on the ORL face database

The ORL database [49] includes 400 face images taken from 40 subjects each providing 10 face images. For some subjects, the images were taken at different times, with varying lighting, facial expressions (open/closed eyes, smiling/not smiling), and facial details (glasses/no glasses). Each image was also resized to a 56 by 46 image matrix by using the down-sampling algorithm. We took the first 1, 2, 3 and 4 face images of each subject as original training samples and treated the remaining face images as test samples. The experimental results were shown in Table 5. We see again that proposed scheme can improve all the methods.

6.3. Experiments on the Yale B face database

In this subsection we use the Yale B [50] and the Extended Yale B [51] face databases to conduct experiments. There are 10 subjects in the Yale B database, and 28 subjects in the extended Yale B database. Each subject has 64 images under different illumination conditions. The facial portion of each original image was cropped to a 192×168 image. We resized the cropped image to a 96 by 84 matrix. In order to computationally efficiently perform improvement to CFKNNC and CFKNNC, we did as follows. Before improvement to CFKNNC and CFKNNC were implemented, the face image was further resized to 48 by 42. We took the first 16, 20 and 24 face images of each subject as original training samples and treated the remaining face images as test samples. Table 6 shows the rates of classification errors (%) of different methods on the Yale B database. The experimental results show again that our proposed scheme can improve all the methods.

Table 6
The rates of classification errors (%) of different methods on the Yale B database.

Number of the training samples of each subject	24	20	16
LRC	16.51	23.33	24.73
Improvement to LRC	12.76	20.93	24.07
INNC	33.29	31.04	31.96
Improvement to INNC	23.95	27.15	31.03
CRC	22.57	24.70	26.86
Improvement to CRC	19.54	21.77	24.01
SRC	40.86	43.18	46.27
Improvement to SRC	35.20	37.20	37.06
CFKNNC	29.28	29.61	31.03
Improvement to CFKNNC	28.68	27.57	29.77

7. Conclusions

Our this paper clearly demonstrates that the mirror image of the face image can be exploited to simulate possible variation of the face image and is able to reduce the side-effect of the pose and illumination difference between the training and test samples of the same face. The proposed scheme can also overcome the misalignment problem of the face image, which usually reduces the accuracy of face recognition. The proposed scheme is very simple and computationally very efficient and improves RBCs at a low computational cost. The analyses and experimental results sufficiently show the rationales of the proposed scheme. As the proposed scheme provides a good way to exploit the special nature of the face and is helpful for achieving better recognition results, it can be also applied to other face recognition methods.

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