Face Recognition Based on Face-Specific Subspace

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ABSTRACT: In this article, we present an individual appearance model based method, named face-specific subspace (FSS), for recognizing human faces under variation in lighting, expression, and viewpoint. This method derives from the traditional Eigenface but differs from it in essence. In Eigenface, each face image is represented as a point in a low-dimensional face subspace shared by *all* faces; however, the experiments conducted show one of the demerits of such a strategy: it fails to accurately represent the most discriminanting features of a specific face. Therefore, we propose to model each face with one individual face subspace, named Face-Specific Subspace. Distance from the face-specific subspace, that is, the reconstruction error, is then exploited as the similarity measurement for identification. Furthermore, to enable the proposed approach to solve the single example problem, a technique to derive multisamples from one single example is further developed. Extensive experiments on several academic databases show that our method significantly outperforms Eigenface and template matching, which intensively indicates its robustness under variation in illumination, expression, and viewpoint. Int J Imaging Syst Technol, 13, 23–32, 2003; DOI 10.1002/ima.10047

Key words: face recognition; eigenface; face-specific subspace; distance from face subspace

1. INTRODUCTION

Face recognition technologies have a variety of potential applications in public security, law enforcement, and commerce, such as mug-shot database matching, identity authentication for credit card or driver license, access control, information security, and intelligent surveillance. In addition, there are many emerging fields that can benefit from face recognition technology, such as the new generation intelligent human-computer interfaces and e-services, including e-home, tele-shopping, and tele-banking. Related research activities have significantly increased over the past few years (Samal and IyenGar, 1992; Brunelli and Poggio, 1993; Chellappa and Wilson, 1995).

As for early researches, geometric feature based methods and template matching methods used to be popular technologies, which were compared in 1992 by Brunelli and Poggio. Their conclusion showed that template matching outperforms the geometric feature based ones (Brunelli and Poggio, 1993). Therefore, since the 1990s, appearance-based methods have been dominant researches, from which two categories of face recognition technology were derived: holistic appearance feature based and analytic local feature based. Popular methods belonging to the former paradigm include Eigenface (Turk and Pentland, 1991; Zhang et al., 1997), Fisherface (Belhumeur et al., 1997), Probabilistic and Bayesian matching (Moghaddam and Pentland, 1995; Moghaddam, 1998, 2000), subspace LDA (Zhao and Chellappa, 2000), and Active Shape/Appearance Models (ASMs/AAMs; Lanitis et al., 1997; Cootes et al., 1998; Edwards et al., 1999) based methods. Local feature analysis (LFA; Penev and Atick, 1996) and Elastic Bunch Graph Matching (EBGM; Zhang et al., 1997; Wiskott et al., 1997) are typical instances of the latter category, among which LFA has been developed to the most successful commercial face recognition system, named FaceIt, by Visionics Corp. FERET evaluation has provided extensive comparisons of these algorithms (Phillips et al., 2000; Pentland, 2000), as well as a kind of evaluation protocol for face recognition systems. More recently, Support Vector Machine (SVM) has also been applied to face recognition successfully (Guo et al., 2000).

However, the performance of almost all current face recognition systems, both academic and commercial systems, is heavily subject to the variance in the imaging conditions (Phillips et al., 2000; Pentland, 2000). It has been discovered by the FERET testing that pose and illumination variations are two bottlenecks for a practical face recognition system. By far, no revolutionary practical solutions are available for these problems. However, some solutions to pose and illumination problems do have emerged including invariant-feature-based methods (Adini et al., 1997), 3D linear illumination subspace (Belhumeur et al., 1997), linear object class (Vetter and Poggio, 1997), illumination and pose manifold (Murase et al., 1995), Symmetric Shape-From-Shading (Zhao and Chellappa, 2000), photometric alignment (Shashua, 1997), Quotient Image (Shashua and Riklin-Raviv, 2001), illumination cones (Georghiades et al., 2001), Lambertian Reflectance and Linear Subspace (Basri and Jacobs, 2001), Eigen light-fields (Gross et al., 2002), and parametric linear subspace (Oakda and v.d. Malsburg, 2002), etc.

Among all these methods for face recognition, Eigenface-based methods have been among the most attractive methods since the 1990s. However, most extensions to Eigenface are focused on the different back-end classifier, instead of the front-end representation of the faces. This article extends the Eigenface method in an essentially different way by proposing the idea to represent each face by using a face-

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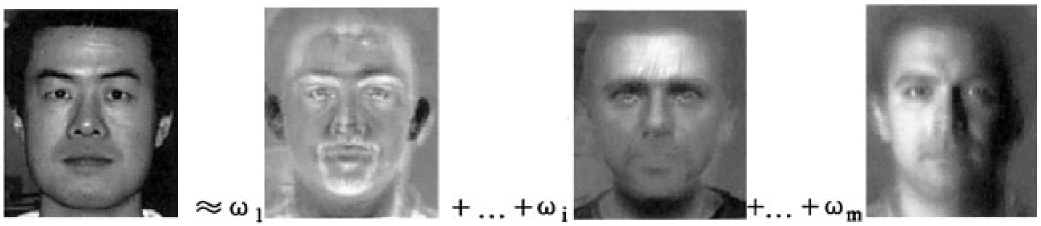


Figure 1. One face image is represented as the linear combination of *m* leading Eigenfaces.

specific subspace (FSS), while in conventional Eigenface method, face images are analyzed on the features extracted in a low-dimensional space learned from "all" the training examples of "all" faces. We argue that FSS can "distill" the common information of the images from the same face, so it can be regarded as the representation of the specific face. Based on the FSS representation, corresponding similarity measure and minimum reconstruction error rule are presented.

For such applications as mug shot matching, suspect recognition, etc., it is normal that only one single face image is available for each person to be recognized. Although the proposed FSS-based method essentially requires multiple examples to learn each FSS, we further propose a simple technique to derive multisamples from a given single face image to endow FSS method with the ability to handle this kind of face recognition problem. Extensive experiments demonstrate the effectiveness of the proposed approaches.

The remaining parts of the article are organized as follows: In Section 2, the FSS-based face recognition method is proposed based on the analysis of some observations on Eigenface method. In Section 3, the FSS-based method is applied to face identification from a single example face image. Extensive comparative experiments are carried out in Section 4. Finally, conclusions are drawn in Section 5.

2. FSS-BASED FACE IDENTIFICATION

2.1. Eigenface Methods. As is well known in the face recognition community, Eigenface is essentially based on the idea that face images can be regarded as points in the high-dimensional image space, and they are believed to approximately cluster as a subspace, so called "face subspace," which can be expanded by some leading Eigenfaces. Figure 1 visually illustrates the idea to represent a face image as the linear combination of the leading Eigenfaces.

A well-known nature is that the Eigenface transform is the optimal transform in the sense of minimum square error (MSE). While it has also been a common sense that the most expressive features (MEF) are not necessarily the Most Discriminating Features (MDF). So, much work has been done to seek the MDF from the gray-level information or from the Eigenface transform (Belhumeur et al., 1997; Moghaddam and Pentland, 1995; Moghaddam, 1998, 2000; Zhao and Chellappa, 2000), among which Fisherface (Belhumeur et al., 1997), subspace LDA (Zhao and Chellappa, 2000), Bayesian matching based on intra/interclass subspace (Moghaddam and Pentland, 1995; Moghaddam, 1998, 2000) are the most successful ones.

Another recognized nature of Eigenface method is that the distance from face subspace (DFFS), i.e., reconstruction error, can be used to detect the occurrence of faces (Turk and Pentland, 1991). It is just this point that inspires us deriving the idea that, reconstruction error can be employed to detect the occurrence of a specific face, if the subspace is learnt from the face examples of the specific face (Shan et al., 2000).

2.2. Further Observations On Eigenface Method. When applying Eigenface to face perceptions, usually only few leading Eigenfaces are used to compute the coefficients on the purpose of dimension reduction, that is, the eigenspace is a quite low-dimensional one. Although the principal eigenspace has been studied thoroughly, little consideration has ever been given to "noise" subspace expanded from the remaining Eigenfaces.

To analyze the properties of the different Eigenfaces, some meaningful experiments are conducted by training one face subspace from 350 faces. Figure 2 illustrates the first 10 and last 10 Eigenfaces visualized. It is obvious that the leading Eigenfaces express all kinds of face patterns, whereas the last ones portray stochastic noisy variance among different faces. The visual effect of Eigenfaces suggests that the leading Eigenfaces "distill" the common patterns of all faces learnt in the training set, whereas the secondary Eigenfaces collect the between-face variance and noise.

Further experiments are conducted to illustrate the effects of different Eigenfaces by reconstructing different input image patterns. As is shown in Figure 3, the patterns in each line, from left to right, are the original patterns and the patterns reconstructed by using the first 50, 100, 150, 200, 250, and 300 Eigenfaces, respectively. In the first line, a face with a salient discriminant characteristic (manmade "mole") is reconstructed, from which we can see that

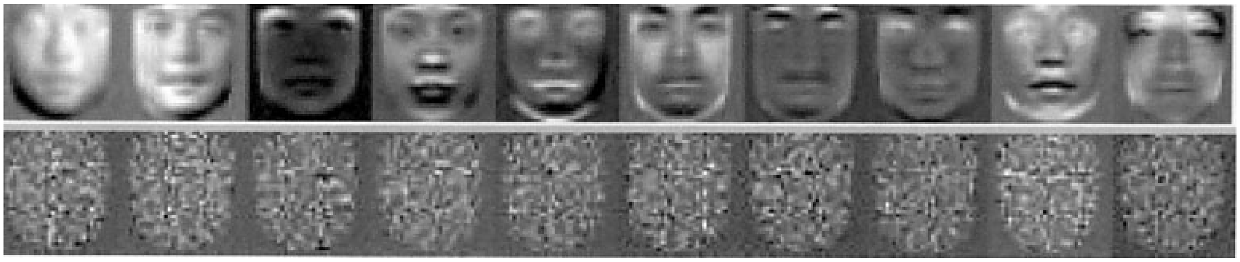
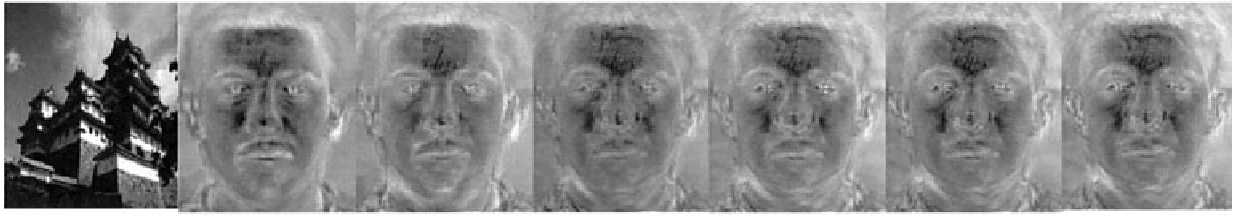


Figure 2. First 10 and last 10 visualized Eigenfaces.

(a) Most discriminant feature is not represented by the Eigenface method. No back-end classifier can compensate this demerit.



(b) Eigenface can hardly represent non-face patterns, which provides the possibility to detect the occurrence of faces.

Figure 3. Demerits and merits of the Eigenface method.

the mole cannot be reconstructed when the leading Eigenfaces are used, which obviously shows the demerit of the Eigenface representation. Note that, since the discriminant features are not modeled by the Eigenface representation, any back-end classifier could compensate the demerits.

The second line in Figure 3 illustrates the ability of the Eigenfaces to reconstruct nonface patterns, in which input pattern is a scene. It is interesting but understandable that it is reconstructed as a "face" pattern. This suggests that the Eigenfaces provide favorable power to discriminate face patterns from nonface patterns.

On the basis of the previous observations, we argue that Eigenface representation may mainly extract the features of the input pattern as a common face, but no individual characteristics that discriminate different persons, and the noise subspace may contain more between-faces difference. So the Eigenface method may be more suitable for the detection of face patterns, that is, less DFFS means more similarity to face pattern. We derive the idea that, based on the point of view, if a subspace is learned from the face examples of one specific face, correspondingly, it can be used to detect the occurrence of the specific face patterns, i.e., less DFFS means more similarity to the given face. So the FSS-based face recognition method is proposed in the following section.

2.3. FSS-based Face Representation. In this section, we propose to represent each face by using one individual face subspace, named FSS, learned from the training images of the

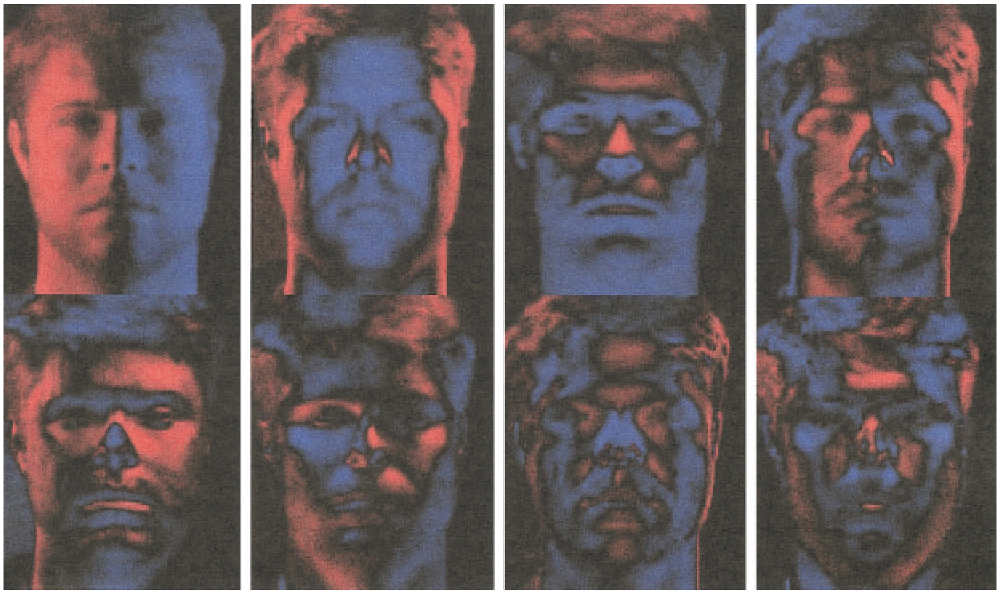
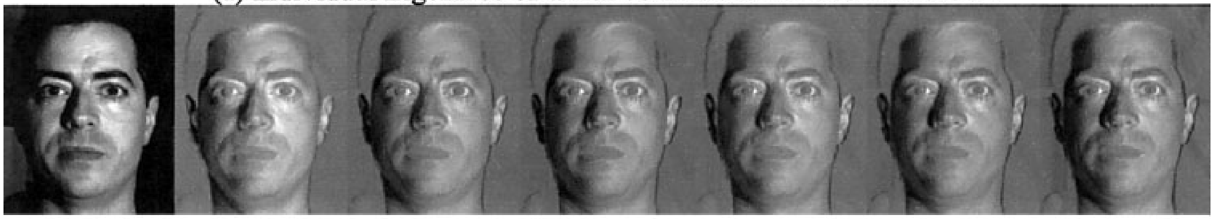
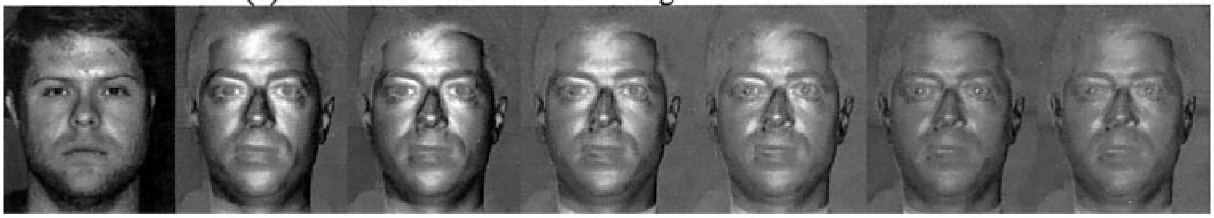


Figure 4. Leading 8 Eigenfaces trained from 64 images of the YaleB01 in Yale face database B. It is very clear that the first Eigenface models the case of left lighting, whereas the third one models the top lighting. The second one models the case of left/right back lighting. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

(a) Individual Eigenface of YaleB06 in the Yale Face Database B



(b) Reconstruction of the face image from the YaleB06 face



(c) Reconstruction of the face image of one Non-YaleB06 (YaleB01)

Figure 5. Eigenfaces of YaleB06 in Yale face database B and its ability to reconstruct different faces.

face. Formally, the FSSs can be learned as the following procedure:

Let the class set of the faces to be identified be as follows:

$$C = \{\Omega_1, \Omega_2, \ldots, \Omega_p\},$$

where p is the number of faces to be recognized. Then for the kth face class Ω_k, $k = 1, 2, \ldots, p$ in C, eigen-decomposition is conducted as

$$U_k^T \sum\nolimits_k U_k = \Lambda_k,$$

where Σ_k is the covariance matrix of the kth face, Λ_k is the diagonal matrix whose diagonal elements are the decreasingly ordered eigenvalues $\lambda_1^k, \lambda_2^k, \ldots, \lambda_{d_k}^k$ of Σ_k, and $U_k = [\mu_1^{(k)}, \mu_2^{(k)}, \ldots, \mu_{d_k}^{(k)}]$ is the matrix formed by the eigenvectors of Σ_k, where $\mu_1^{(k)}, \mu_2^{(k)}, \ldots, \mu_{d_k}^{(k)}$ are eigenvectors corresponding to eigenvalues $\lambda_1^k, \lambda_2^k, \ldots, \lambda_{d_k}^k$, respectively. So the following bases matrix spans the kth FSS:

$$U_k = (\mu_1^{(k)}, \mu_2^{(k)}, \ldots, \mu_{d_k}^{(k)}).$$

To sum up, the kth face is represented as a *4*-tuple, that is the kth FSS, by

$$\Re_k = (U_k, \Psi_k, \Lambda_k, d_k),$$

where Ψ_k is the mean of the kth face, and d_k is the dimension of the FSS.

Figure 4 visualizes the leading Eigenfaces of a specific face, YaleB01 from Yale Face Database B. Its FSS is trained from all the 64 images viewed under the frontal pose and 64 different lighting conditions. These Eigenfaces are visualized colorfully, in which red means positive values, whereas blue means negative values. From these individual Eigenfaces, distinct facial characteristics of the face can be clearly seen. At the same time, obviously, most within-class variations due to lighting conditions are modeled accurately. Therefore, the FSS-based method is expected to be robust to the lighting variance. Our experiments in Section 4.2 strongly support this conclusion.

2.4. Identify Faces Based on FSS. After FSS for each face is learned, similar to DFSS in Eigenface method, the similarity of any image to a face can be measured by using the Distance From FSS (DFFSS): less DFFSS means more probability that the image belongs to the corresponding face. It can be formulated as follows:

Let Γ be any input image. It can be projected to the kth FSS by

$$W^{(k)} = U_k^T \Phi^{(k)}, \quad \text{where } \Phi^{(k)} = \Gamma - \Psi_k.$$

Then $\Phi^{(k)}$ can be reconstructed by

$$\Phi_r^{(k)} = U_k W^{(k)}$$

So, Γ's distance from kth FSS (DFFSS) is computed as the following reconstruction error:

$$\varepsilon^{(k)} = \|\Phi^{(k)} - \Phi_r^{(k)}\|.$$

The DFFSS reflects the quantity of the kth face pattern "hiding" in the input image Γ, or in other words, the power of the kth FSS to reconstruct the input pattern Γ. So it can be regarded as the similarity of the input pattern Γ to the face corresponding to the kth FSS.

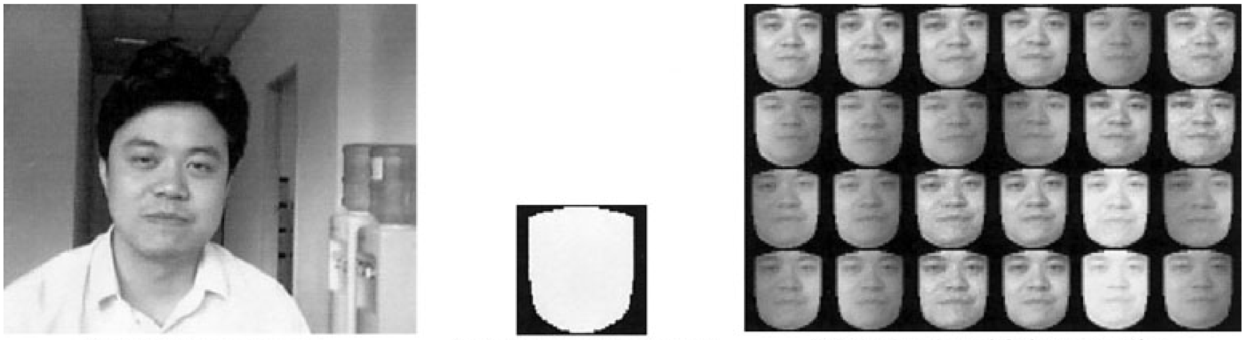

(a) Input face image (b) Face masked used (c) derived multiple examples

Figure 6. Deriving multiple samples from single image.

Therefore, the following minimal distance classifier can be naturally formulated:

$$\Gamma \in \Omega_m \quad \text{if } \varepsilon^{(m)} = \min_{l \le k \le p}\{\varepsilon^{(k)}\}.$$

To demonstrate the rationality of the above recognition strategy intuitively, further reconstruction experiments are conducted on FSS for different input patterns. To get comparable visual effects, the reconstruction is carried out by the following formula:

$$\Gamma' = \|\Gamma - \Psi^{(k)}\| \cdot (\Phi_r^{(k)} + \Psi^{(k)}).$$

Figure 5 illustrates the power of one specific FSS to reconstruct various input patterns. The first line shows the leading 7 Eigenfaces of YaleB06 in Yale face database B, trained from his 64 face images under 64 different lighting conditions. Lines 2–4 show its ability to reconstruct different face patterns. The first columns in lines 2 to 4 are the input patterns. The subsequent pictures in each line illustrate the reconstructed patterns by using the leading 10, 20, 30, 40, 50, and 60 Eigenfaces of YaleB06. The input face image in line 2 belongs to YaleB06, and it can be clearly seen that its reconstructed faces are quite similar in appearance to the input face, that is, with small DFFSS. Although the input face images in lines 3 and 4 are from non-YaleB06 faces, therefore it is obvious that the reconstructed faces are quite different from the corresponding input face but still very similar to the face YaleB06, so, much more difference between the input pattern and reconstructed ones can be observed, that is, with large SFFSS.

Obviously, FSS has the favorable nature to reconstruct its own face patterns perfectly; however, that is not the case for face images of other faces. This strongly suggests that the FSS-based face representation has excellent class discriminating power.

3. FACE RECOGNITION FROM SINGLE EXAMPLE IMAGE

As we know, to learn a face subspace, multiple training example images are required. For FSS, it means more than one example per face is needed to train his/her FSS. But for some face recognition applications, such as mug shot matching, suspect identification, etc., only few (even single) face images are available for each subject involved; therefore, the FSS-based method cannot be applied to them directly. To solve this problem, we further propose a simple technique to derive multiple samples from a single example image. The technique is based on the following two intuitive propositions (Shan et al., 2002):

1. Proper geometric transforms, such as translation, rotation in image plane, scale changes, etc., do not change the identity attribute of a face image visually.
2. Proper gray-level transforms, such as simulative directional lighting, man-made noise, etc., do not change the identity attribute of a face image visually.

In the proposed technique, the two kinds of transforms are combined to derive tens of training examples from single example image, which are then fed into the FSS learning procedure. Figure 6(c) illustrates some normalized "virtual" example images derived from one face image as shown in Figure 6(a) by using our techniques.

In the following experiments, we use "FSS" to denote the FSS method without enlarging training set and "FSS+" to denote the method of enlarging the training set by deriving multiple samples from one example image. The similar notation method is exploited for Eigenface and Correlation.

4. EXPERIMENTS

To verify the effectiveness of the proposed approaches, we also develop Eigenface method and template matching as benchmarks.

Figure 7. Normalized faces

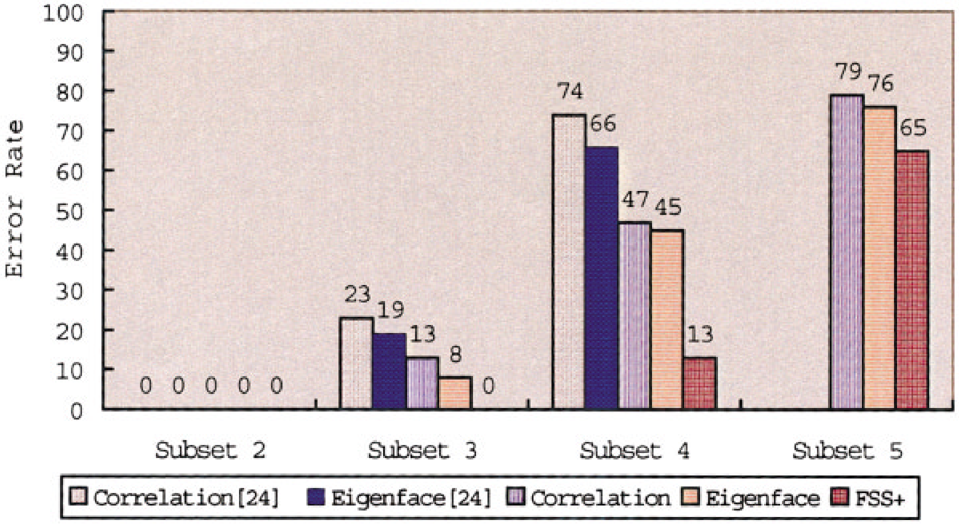


Figure 8. Experimental results on Yale Face Database B. Note: Since Georghiades et al. (2001) does not test on Subset 5, they are absent for subset 5. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

Extensive experiments are conducted on Yale Face Database B, Yale database, Bern multi-pose database, and our own face database containing 350 different subjects under some variances in lighting conditions, pose, and facial expressions.

4.1. Face Alignment and Benchmark Designs. Eigenface and template matching method are de facto the standard benchmarks in the face recognition community. They are also used as benchmarks in FERET evaluation (Phillips et al., 2000). Their performance can reflect the difficulty of the given face recognition task to a certain extent.

Face Normalization. In this article, to alleviate the influence of translation, ration, lighting and scale variance, for all methods tested, faces are normalized by geometric and photometric normalization. As to geometric normalization, the locations of the two irises are first localized manually and then placed at fixed locations by affine transformation. A mask, as shown in Figure 6(b), is overlapped over the face region to eliminate the alterable background and hairstyle. Finally all faces are warped to the size of 32 × 32 as shown in Figure 7. Histogram equalization is conducted to normalize illumination, and all the face data are vectorized to unit length before they are fed into the training or testing procedure.

Eigenface Method. We design the Eigenface method according to Turk and Pentland (1991). All faces are normalized as in Figure 7. The training set used to learn the common face subspace is just the gallery set constituted by all the training images of all the faces. Furthermore, some improvements are taken including discarding the first few Eigenfaces and compute similarity based on cosine measure. As to the dimension of the Eigenface method, we have conducted experiments for all possible dimensions to choose the best dimension. Therefore, in our experiments, the performances of the Eigenface method are all the best case after considering the dimension, the distance mode and with/without some leading dimensions. We have elaborately designed the Eigenface method, which can be proved from the better performance of our Eigenface implementa-

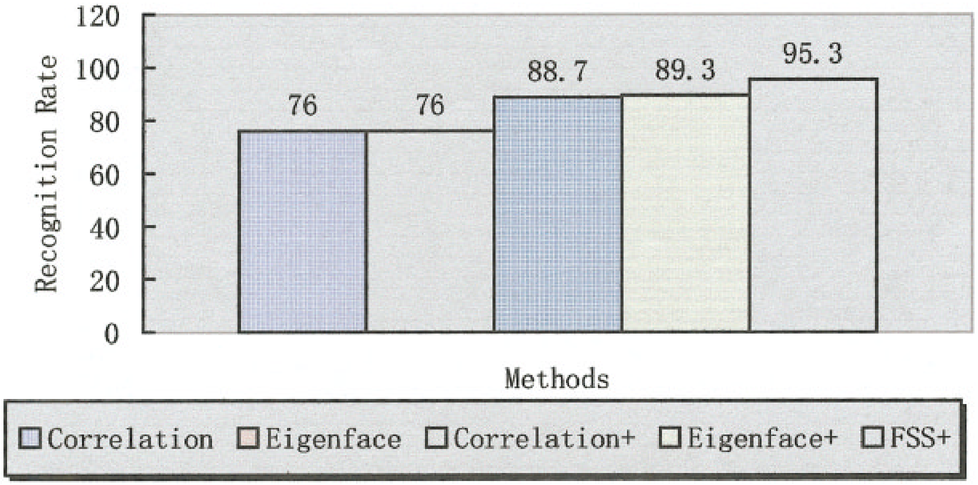


Figure 9. Performance comparisons on Yale face database. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

Table I. Comparisons with methods in Belhumeur et al. (1997).

"Leave-One-Out" (nine examples per subject for train)		One example per subject for train	
Methods in Belhumeur et al. (1997)	Error Rate (Copped)		Methods in this article
Eigenface (W/O 1st 3)	15.3		
Correlation	23.9	24.0	Correlation
Subspace	21.6	24.0	Eigenface
Fisherface	7.3	4.7	FSS+

Note: Quoted data are from Belhumeur et al. (1997). However, this comparison is unfair to our methods, because we use one example per face, while Belhumeur et al. (1997) use nine or ten examples per face.

tion than the performance of the Eigenface in Georghiades et al. (2001).

Because we have derived multiple training samples from one example, to compare fairly the performance of the different methods, we have also enlarged the training set of the Eigenface method. In the following experiments, we use "Eigenface+" to stand for this case, while "Eigenface" is used as the standard Eigenface method.

Template Matching. Template matching is operated on the normalized faces as shown in Figure 7. Similarity between two faces is measured by using the cosine of the angle between the two vectors, denoted as $\mathrm{Cos}(\theta)$. Similar to the Eigenface method, we use "Correlation+" to denote the case of enlarging the training set and "Correlation" to denote the case without enlarging the training set.

4.2. Experiments On Yale Face Database B. To verify the performance of the proposed method to lighting variation, we have conducted experiments on Yale Face Database B as described in Georghiades et al. (2001), which is a face database with complete lighting variance. Only the frontal pose for each individual is used in this article, including 640 images from 10 individuals, with 64 images per person acquired under 64 different lighting conditions. The same strategy as in Georghiades et al. (2001) is adopted to divide the images of each individual into 5 subsets. Then we crop the images according to the eye coordinates as in Figure 7. In our experiments, one FSS is trained for each face by the 7 images in his/her subset 1 as in Section 2, and the images in other subsets are tested. The experimental results are shown in Figure 8. The training set for each face is also enlarged by deriving multiple samples from each training face image.

From Figure 8, much improvement is observed for FSS compared with correlation and Eigenface methods, which impressively indicate the robustness and effectiveness of the proposed method to variances in lighting conditions. Also, from Figure 8 we can clearly see that our Eigenface and correlation methods are elaborately designed.

4.3. Experiments On Yale 15 Subjects Face Database. The Yale face database contains 165 images from 15 subjects, with 11 images per subjects, among which there is a normal face with neutral expression, taken under ambient lighting conditions, whereas the left 10 images cover different cases including faces with/without glasses, images with basic expressions (happy, sad, sleepy, wink, surprised), and images illuminated by center-light, left-light, and right-light. All faces are frontal views [Refer to Belhumeur et al. (1997) for details.]

In our experiment, all the 15 normal face images (one for each subject) are chosen to form the training set and gallery set, and all the other images (150 images) constitute the probe set for all the algorithms tested. For our FSS-based method, 15 FSSs are learned, respectively, from the 15 normal face images as described in Section 2 and Section 3. For Eigenface method, the 15 normal faces are used to train a face subspace, and then they are projected to the subspace to extract Eigenface features, which are stored as reference templates for a nearest neighbor classifier. For template matching approach, the normalized 32×32 face images cropped from the 15 normal face images are stored as templates and the normalized correlation is computed as similarity measurement. And Eigenface+ and Correlation+ are trained by the same enlarged training set as used in our FSS. The performances of these methods are plotted in Figure 9. It is clear that our proposed method outperforms the other approaches. The Rank-1 (first-choice) recognition ration of our method is 95.3% whereas that of Eigenface+ method is 89.3% and that of Eigenface is 76%. No obvious difference occurs between Eigenface and correlation method.

A well-known article with experiments on Yale face database is Belhumeur et al. (1997), in which the Fisherface method was proposed. Note that the setup of our experiments is quite different from that article, where error rates were determined by the "Leave-One-Out" strategy. But relative performance can still be compared as shown in Table I. When comparing these data, readers must note that, in the "Leave-One-Out" strategy, *ten* training examples are learned for each subject, except for the test person who is represented by *nine* ones (Belhumeur et al., 1997). However, in our methods only *one* example image for each subject is provided for the training procedure. It is obvious that our case is much more difficult than the "Leave-One-Out" strategy. Nevertheless our method outperforms all the other methods tested. Imaginably, if the methods in this article were tested by the Leave-One-Out strategy, much better

Figure 10. The 10 examples of one subject in the Bern face database.

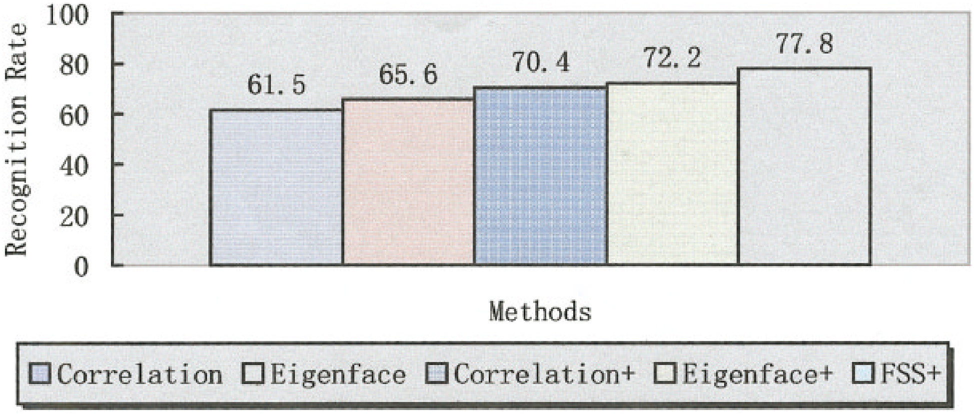


Figure 11. Performance comparison of different algorithms on Bern 30 subjects face database. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

performance than those in Belhumeur et al. (1997) should be observed.

4.4. Experiments on Bern 30 Subject Multipose Face Database. To verify the effectiveness of the proposed framework on multi-pose face recognition problem, comparative experiments are conducted on Bern 30 subjects multiple poses face database. The Bern database consist of 300 examples images of 30 subject, for each person 10 gray-level images with slight variations of the head positions (1,2 right into the camera; 3,4 looking to the right; 5,6 looking to the left; 7,8 downwards; 9,10 upwards; © 1995 University of Bern All Rights Reserved). The 10 examples of one subject are shown in Figure 10.

In our experiments, the No. "1" examples (looking right into the camera) of each subject in the database are chosen as the example images to form the training set (30 examples totally). As for our FSS-based method, one FSS for each subject is learnt from his/her No. 1 example image. As to the Eigenface method, its common subspace is trained from all the 30 examples, and their projections to the common subspace are stored as reference Eigen-features template. Correlation is conducted all the same as in Yale experiments. Their performances are shown in Figure 11. From Figure 11, we can find that our FSS-based method outperforms other algorithms, because the first-choice recognition rate of our method is 77.8%, whereas Eigenface method is 65.6% and Eigenface+ is 72.2%. Correlation has similar performance as Eigenface.

4.5. Experiments on Our 350 Subjects Face Database. To further demonstrate the performance and scalability of our FSS-based method on larger database, more detailed experiments are conducted on a 350 subjects face database. For the 350 subjects, 1750 images are acquired, with 5 images per subject. All images are taken with a general USB camera. For each subject, 1 normal face (nearly frontal, neutral expression, and ambient lighting condition) is chosen as the training example; therefore, a training/gallery set containing 350 faces is constructed. All the remaining 1400 images (4 examples per subject) constitute the probe set, which cover face images with different expressions, lighting conditions, and slight pose variance. Obvious difference can easily be seen between the images in the gallery set and the probe set. Figure 12 shows some examples images in our face database. Figure 13 illustrates the performances of the different methods tested. As shown in Figure

Figure 12. Examples from our face database. The first image are for training in each line, and the other four image are used for testing.

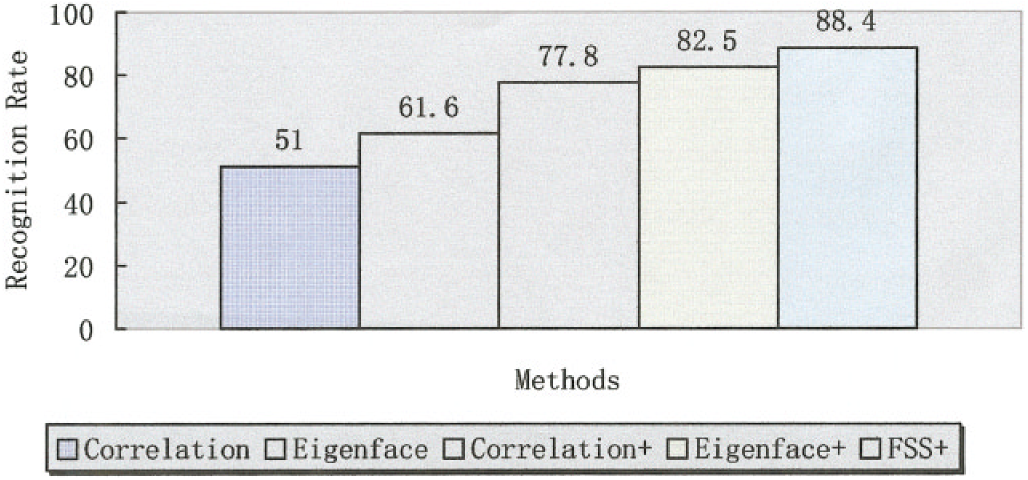


Figure 13. Performance comparison of different algorithms on our 350 subjects face database. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

13, apparently the proposed method outperforms all other algorithms. The recognition rate of our method is 88.4%, whereas that of the Eigenface method is 61.6% and that of the Eigenface+ is 82.5%.

4.6. Observations on Experimental Results. These experiments on the several face databases clearly indicate the outstanding performance of our FSS(+)-based method compared with two benchmark algorithms. The results sufficiently demonstrate the adaptability and scalability of our method to expression, lighting, and slight pose variance; because the Yale face database B is a database with complex lighting conditions, the Yale database covers various expressions and varying illuminations and our database contains 350 subjects with various expressions and varying poses. These results have strongly supported our previous expectation, that is, FSS-based face representation has excellent class discriminating power.

5. CONCLUSIONS AND FUTURE WORKS

We propose in this article to represent a face by using FSS and present the FSS-based face recognition method. We argue that Eigenface representation may mainly extract the common features of all faces, but not individual characteristics that discriminate different persons, and the "noise" subspace may contain more useful interfaces difference. So the Eigenface method may be more suitable for the detection of face patterns. Therefore, we derive the FSS-based face recognition method: one individual subspace is learned from the face examples of each face and used to detect the occurrence of the specific face patterns by using the DFFSS, that is, the reconstruction error. Aiming at face recognition from single example image, a technique is further proposed to derive multiple samples from single example image and endow the FSS-based method the ability to recognize face from one example image.

Extensive experiments one several face database demonstrate the excellent performance of our new method over conventional benchmarks under variations in expression, illumination, and viewpoint. Though the proposed method requires more storage for each face and more time to recognize one face; however, its computational complexity is linear and the recognition can be thoroughly conducted in parallel.

Future efforts will be devoted to more deliberate virtual views synthesis algorithms to derive multiple samples from single example view. Recent developments in face relighting technologies have provided the possibility to generate virtual views under arbitrary lighting conditions and pose.

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