Performance Improvement of Face Recognition Algorithms Using Occluded-Region Detection

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Abstract

Facial occlusions such as eyeglasses, hairs and beards decrease the performance of face recognition algorithms. To improve the performance of face recognition algorithms, this paper proposes a novel framework of face recognition combined with the occluded-region detection method. In this paper, we detect occluded regions using Fast-Weighted Principal Component Analysis (FW-PCA) and use the occluded regions as weights for matching face images. To demonstrate the effectiveness of the proposed framework, we use two face recognition algorithms: Local Binary Patterns (LBP) and Phase-Only Correlation (POC). Experimental evaluation using public face image databases indicates performance improvement of the face recognition algorithms for face images with natural and artificial occlusions.

1. Introduction

Recently, face recognition has been an area of intense research in the field of biometric recognition [9]. The major problem in face recognition is to recognize face images with illumination change, head pose change, facial expression change and occlusion. Many face recognition algorithms dealing with the above problem have been proposed even now. In this paper, we focus on improving the performance of face recognition algorithms for face images with/without occlusion such as eyeglasses, hairs and beards. The performance of face recognition algorithms is decreased due to occlusions in face images. Hence, it is required to take into account of occluded regions in face image matching.

So far, the occluded-region detection methods have been proposed in Refs. [11, 22, 10, 15, 18, 19, 13, 5]. These methods are classified into two types: model-based and appearance-based approaches. The model-based approaches [22, 18, 19] extract facial feature points using the face model such as Active Appearance Model (AAM) [4], and detect occluded regions depending on the position of extracted feature points. The occluded regions can be detected if the model fitting is successfully applied, while the face model may not be accurately fit on the occluded regions. The appearance-based approaches [11, 10, 15, 13, 5] detect occluded regions using texture information of face images. Most appearance-based approaches employ image reconstruction using Principal Component Analysis (PCA). The appearance-based approaches are successfully applied if the occluded regions is not too large compared with the face region, while the detection accuracy of occlusion for the appearance-based approaches may be lower than that for the model-based approaches. In this paper, we detect the occluded regions using Fast-Weighted PCA (FW-PCA) proposed in Ref. [5] due to its simplicity and fast computation.

To improve the performance of face recognition algorithms, we propose a novel framework of face recognition combined with the occluded-region detection method. In the proposed framework, we use the occluded regions as matching coefficients or masks for matching face images. To address the problem in face images with/without occlusions, some works have been reported [21, 13]. The algorithms proposed in Refs. [21, 13] detect block-wise occluded region for the exclusive use of the face recognition algorithm. On the other hand, the proposed approach detects the pixel-wise occluded region which can be used to determine matching coefficients depending on face recognition algorithms. In addition, if necessary, the proposed method can restore occluded regions of the face image for the subsequent face image processing. The effectiveness of the proposed framework is demonstrated by using two face recognition algorithms such as Local Binary Patterns (LBP) [3] and Phase-Only Correlation (POC) [6]. Through a set of experiments using public face databases such as FERET Database [16], AT&T Face Database [1], Yale Face Database A [2] and AR Face Database [12], the proposed framework exhibits performance improvement of face recognition algorithms for face images with natural and artificial occlusions.

2. Occluded-Region Detection Using FW-PCA

This section describes the occluded-region detection method used in this paper. We present the fundamentals of FW-PCA and the occluded-region detection method using FW-PCA.

2.1. FW-PCA

In this subsection, we briefly explain the fundamentals of FW-PCA proposed in Ref. [5].

In general, PCA-based image reconstruction [8] is performed by

$$\hat{\mathbf{x}} \simeq \mathbf{E}\mathbf{p} \quad \left(\hat{x}_i \simeq \sum_{d=1}^{D} e_{di} p_d\right), \tag{1}$$

where $\hat{\mathbf{x}}$ is the reconstructed image, $\mathbf{E}$ is the eigenspace consisting of eigenvectors $[\mathbf{e}_1^T \ \mathbf{e}_2^T \ \cdots \ \mathbf{e}_D^T]$ which are calculated from the training image set, and D is the number of eigenvectors. $\mathbf{p}$ is the vector of principal component scores calculated by

$$\mathbf{p} = \mathbf{E}^{\mathrm{T}}\mathbf{x} \quad \left(p_d = \sum_{i=1}^{N} e_{di} x_i\right), \tag{2}$$

where $\mathbf{x}$ is the input image and N is the number of pixels. The d-th principal component score p_d is calculated by the inner product of the input image $\mathbf{x}$ and the d-th eigenvector $\mathbf{e}_d$ as follows

$$p_d = \sum_{i=1}^{N} e_{di} x_i = \|\mathbf{e}_d\| \|\mathbf{x}\| \cos\theta_d, \tag{3}$$

where $\|\mathbf{x}\|$ and $\|\mathbf{e}_d\|$ indicate the amplitude of the input image and the d-th eigenvector, respectively. $\cos\theta_d$ indicates the correlation coefficient between the input image and the d-th eigenvector. When the image has missing pixels, i.e., occlusion, the principal component score $\hat{\mathbf{p}}$ having minimum reconstruction error is estimated by using the least squares optimization. Hence, the principal component score $\hat{\mathbf{p}}$ cannot be directly calculated.

To reduce the computation time of estimating the principal component score, FW-PCA directly calculates the principle component score $\hat{\mathbf{p}}$ only from the effective pixels by approximating the calculation of $\cos\theta_d$ and $\|\mathbf{x}\|$ in Eq. (3). The correlation coefficient $\cos\theta_d$ is defined by

$$\cos\theta_d = \frac{\sum_{i=1}^{N} e_{di} x_i}{\sqrt{\sum_{i=1}^{N} x_i^2}\sqrt{\sum_{i=1}^{N} e_{di}^2}}. \tag{4}$$

By introducing the weight $\mathbf{w} = [w_1 \ w_2 \ \cdots w_N]^{\mathrm{T}}$, where each element w_i is assigned 1 for the effective pixel or 0 for the missing pixel, the approximated correlation coefficient $\cos\hat{\theta}_d$ is defined by

$$\cos\hat{\theta}_d = \frac{\sum_{i=1}^{N} w_i e_{di} x_i}{\sqrt{\sum_{i=1}^{N} w_i x_i^2}\sqrt{\sum_{i=1}^{N} w_i e_{di}^2}}. \tag{5}$$

Similarly, by introducing the weight $\mathbf{w}$, the relation between $\|\mathbf{x}\|$ and $\|\mathbf{e}_d\|$ is derived as follows

$$\frac{\|\mathbf{x}\|}{\|\mathbf{e}_d\|} \simeq \frac{\sqrt{\sum_{i=1}^{N} w_i x_i^2}}{\sqrt{\sum_{i=1}^{N} w_i e_{di}^2}}. \tag{6}$$

Using the above relation, the approximated amplitude $\|\hat{\mathbf{x}}\|$ is defined by

$$\|\hat{\mathbf{x}}\| = \frac{\sqrt{\sum_{i=1}^{N} w_i x_i^2}}{\sqrt{\sum_{i=1}^{N} w_i e_{di}^2}}\sqrt{\sum_{i=1}^{N} e_{di}^2}. \tag{7}$$

Replacing $\cos\theta_d$ and $\|\mathbf{x}\|$ with Eq. (5) and Eq. (7), respectively, Eq. (3) can be rewritten as

$$\hat{p}_d = \|\mathbf{e}_d\| \|\hat{\mathbf{x}}\| \cos\hat{\theta}_d = \frac{\sum_{i=1}^{N} w_i e_{di} x_i}{\sum_{i=1}^{N} w_i e_{di}^2} \sum_{i=1}^{N} e_{di}^2. \tag{8}$$

Using the above equation, we can calculate the weighted PCA without least squares optimization even for the image having the missing pixels.

2.2. Occluded-Region Detection Using FW-PCA

This subsection presents the occluded-region detection method used in this paper. Our method is slightly different from the method proposed in Ref. [5], since the purpose of Ref. [5] is to restore the occluded regions of the face image, while our purpose is to detect the occluded regions. Fig. 1 shows a flow diagram of the occluded-region detection method using FW-PCA used in this paper.

The eigenspace $\mathbf{E}$ is computed using the training images with no occluded region in advance. The standard deviation of the reconstruction error for each pixel $\sigma = [\sigma_1 \ \sigma_2 \ \cdots \sigma_N]^{\mathrm{T}}$ is also computed.

First, the initial weight for FW-PCA is determined using S random weight patterns, where randomly selected M

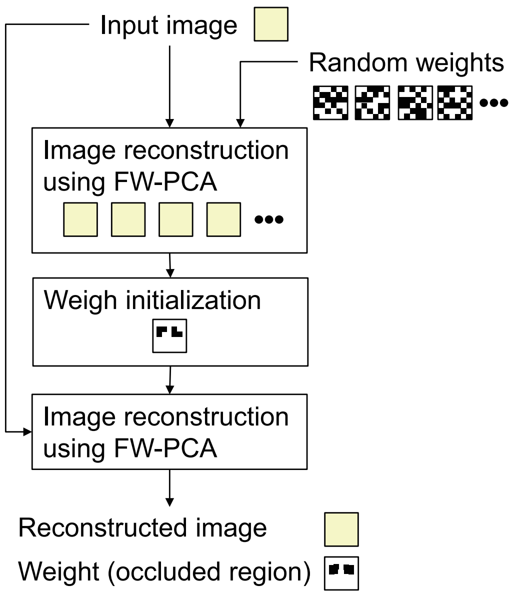

Figure 1. Flow diagram of occluded-region detection using FW-PCA.

pixels are assigned 1 for each weight pattern. The reconstructed image $\hat{\mathbf{x}}_s$ $(s = 1, \cdots, S)$ for each weight pattern is obtained by using FW-PCA. Then, the reconstruction error $\mathbf{e}_s$ between $\mathbf{x}$ and $\hat{\mathbf{x}}_s$ is calculated by

$$\mathbf{e}_s = |\mathbf{x} - \hat{\mathbf{x}}_s|. \tag{9}$$

i-th pixel of $\hat{\mathbf{x}}_s$ is regarded as a missing pixel, if the reconstruction error e_{si} satisfies the following condition:

$$e_{si} > \mu_s \bar{e}_s \quad \text{or} \quad e_{si} > \bar{e}, \tag{10}$$

where $\bar{e}_s$ is the average of the reconstruction error $\mathbf{e}_s$, $\bar{e}$ is the average of all the reconstruction errors, and μ_s is a parameter value depending on $\bar{e}_s$. Among the effective-pixel candidates, K pixels are selected in ascending order of the reconstruction error $\mathbf{e_s}$ as a set of effective pixels of the initial weight $\mathbf{w}$.

We reconstruct the input image $\mathbf{x}$ using FW-PCA with the initial weight $\mathbf{w}$. Comparing $\hat{\mathbf{x}}$ and $\mathbf{x}$, the weight $\mathbf{w}$ is updated by

$$w_i = \begin{cases} 1 & \text{if } |\hat{x}_i - x_i| < \theta_i \\ 0 & \text{otherwise} \end{cases} \quad (i = 1, \cdots, N), \tag{11}$$

where $\theta_i = \eta\sigma_i$ is the threshold for each pixel and η is a coefficient for σ_i. After T-time iterations of the above process, we obtain the reconstructed image $\hat{\mathbf{x}}$ and the weight $\mathbf{w}$, i.e., the occluded regions in the input image.

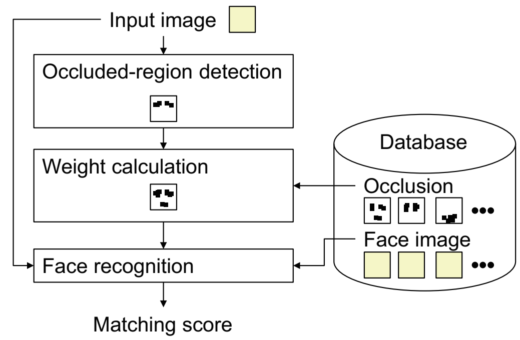

Figure 2. Flow diagram of the proposed face recognition framework with occluded-region detection.

3. Face Recognition Algorithm with Occluded-Region Detection

This section describes the proposed face recognition framework with occluded-region detection method mentioned in the above section.

The main idea of improving the performance of face recognition algorithms is to use the detected occlusion as the coefficients or masks for matching face images. Fig. 2 shows the flow diagram of the proposed face recognition framework. First, we detect the occluded regions in the input image using the method described in Sect. 2.2. Next, comparing the occluded-region of input and registered images, the coefficients or masks for the face recognition algorithm are determined. For example, the most simple way is to use the AND operation between the occluded-region of input and registered images. Thus, we can recognize face images using only the common effective information of input and registered face images.

In this paper, we apply the proposed framework to two types of face recognition algorithms such as LBP [3] and POC [6], and demonstrate the effectiveness of the proposed framework.

3.1. Local Binary Pattern (LBP)

LBP is one of the feature descriptors and has been successfully applied to many computer vision problems [17]. LBP is obtained by thresholding neighborhoods of each pixel with the center pixel value and then the histogram of LBPs is used as a feature descriptor. Ahonen et al. [3] have proposed the face recognition algorithm using LBP.

The procedure of the LBP-based face recognition algorithm is simple. First, the face region is detected, the feature points on the face are detected, and then the scale, rotation and translation are normalized according to the position of feature points. Next, LBP is calculated for each local block image. Finally, the matching score is calculated using the weighted Chi square distance between histograms of LBPs.

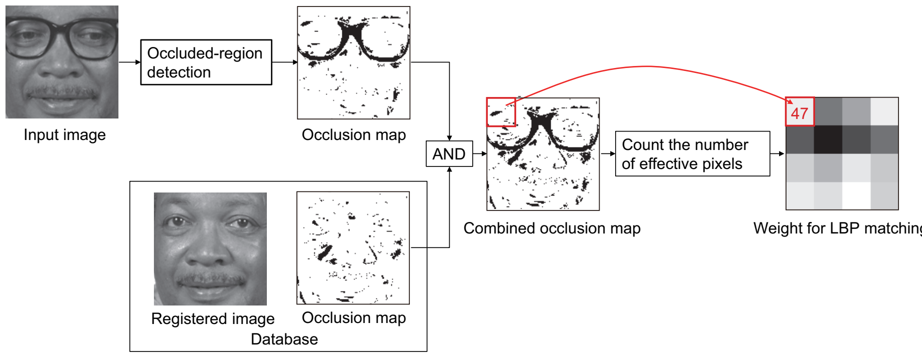

Figure 3. Flow diagram of determining the optimal weight for LBP matching.

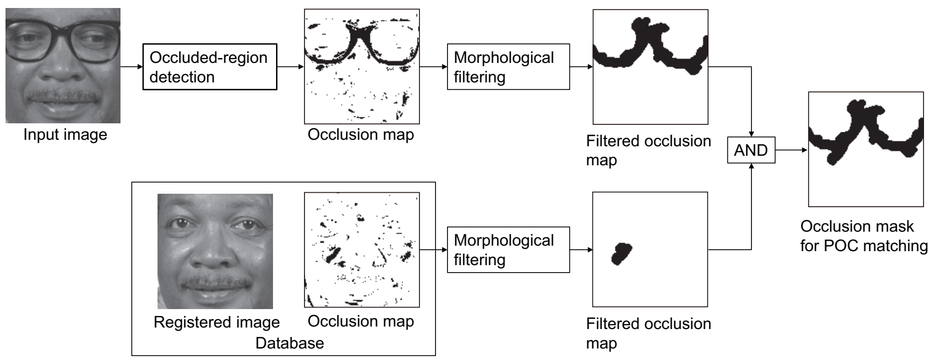

Figure 4. Flow diagram of determining the occlusion mask for POC matching.

If the image has occluded region, the matching score of the LBP matching is decreased even for the genuine pair.

To improve the performance of LBP matching for face images with occlusions, we determine the optimal weight as shown in Fig. 3. First, the occlusion map is obtained from the input image using the occluded-region detection method. Next, the combined occlusion map is calculated by the AND operation between the occlusion maps of the input and registered images. In the combined occlusion map, the black pixel indicates that either the input image or the registered image has the missing pixel, while the white pixel indicates that both images have the effective pixel. The weight for LBP matching is determined as the number of effective pixels for each local block. The small weight means that the local block includes a large occluded region, while the large weight means that the local block includes a small occluded region. The obtained weight is used in the computation of the weighted Chi square distance between LBP histograms. Using the weight obtained from the above procedure, we can perform the accurate LBP matching even for face images with occlusions.

3.2. Phase-Only Correlation (POC)

POC, which is sometimes called phase correlation, is one of the image matching techniques and has been successfully applied to biometric authentication [14, 6] and computer vision problems [7, 20]. The POC function is defined as the inverse Discrete Fourier transform of the normalized cross-power spectrum. The height and position of the correlation peak indicate the similarity and translational displacement between images, respectively. Ito et al. [6] have proposed the face recognition algorithm using POC.

The procedure of POC-based face recognition algorithm is also simple. First, the face image is normalized as well as the first step of the LBP-based face recognition algorithm. Next, a set of the reference points is placed on the face image to evaluate the local block similarity. Using the phase-based correspondence matching, the corresponding point pairs are obtained, where the corresponding point pair having low similarity value is eliminated as an outlier. Finally, the matching score is calculated as the number of correct corresponding point pairs. If the image has occluded region, the matching score of the POC matching is decreased even for the genuine pair.

To improve the performance of POC matching for face images with occlusions, we introduce the occlusion mask as shown in Fig. 4. First, the occlusion map is obtained from the input image using the occluded-region detection method. Next, the morphological filter is applied to the occlusion maps of the input and registered images. In this

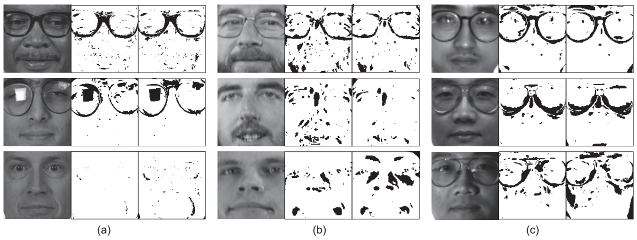

Figure 5. Examples of face images for each database: (a) FERET, (b) AT&T and (c) Yale (left: face image, center: occlusion map obtained by FR-PCA and right: occlusion map obtained by FW-PCA).

Table 1. Parameters for FW-PCA used in this paper.

# of dimensions D	64
# of random patterns S	1,024
# of randomly selected pixels M	64
# of effective pixels K	512
# of iterations T	4
Coefficient η	1.8

Table 2. Parameters for the LBP-based face recognition algorithm.

Type of LBP	$\mathrm{LBP}_{8,2}^{u2}$
# of windows	7×7
Weight of original implementation	Same in Ref. [3]

paper, we apply the bottom-hat and erosion operations to remove the small occluded regions. Then, the occlusion mask is calculated by the AND operation between the filtered occlusion maps of the input and registered images. This mask is used to the reference point placement of the POC-based face recognition algorithm. The reference point is not set to the black pixels of the occlusion mask to prevent the POC matching on the occluded region. Using the occlusion mask obtained by the above procedure, we can perform the accurate POC matching even for face images with occlusions.

4. Experiments and Discussion

This section describes the performance evaluation of the proposed face recognition framework using the public face image databases. In this paper, we use three databases: FERET Database [16], AT&T Face Database [1] and Yale Face Database A [2]. For each face image, we detect the facial feature points using the facial landmark detection method [23] and extract the normalized face region with 128×128 pixels. Fig. 5 shows the examples of normalized face images for each database. We select 1,124 face images having no occlusion from FERET database as the training images for the occluded-region detection method.

We evaluate the performance of the proposed face recognition framework by the Receiver Operating Characteristic (ROC) curve and Equal Error Rate (EER), i.e., verification tests. From each database, we randomly select 300 genuine and 1,000 impostor pairs. Note that the genuine and impostor pairs for FERET database do not include the training images for FW-PCA. Tables 1, 2 and 3 show the parameters for FW-PCA, LBP and POC used in the experiments.

Table 3. Parameters for the POC-based face recognition algorithm.

# of reference points	100
Size of local image block	32×32 pixels
Spectrum weighting function	Gaussian ($\sigma = 0.5$)
# of layers	4

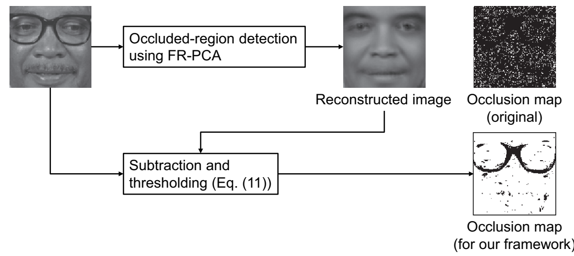

Figure 6. Occlusion map generation using FR-PCA: Original occlusion map dose not represent the complete occluded region. Applying Eq. (11) to the reconstructed image, the occlusion map for our framework is generated.

In order to compare the performance of occluded-region detection, we employ FR-PCA [18, 19] as the conventional method. This method reconstructs the occluded regions using the general PCA with the eigenvectors generated from a set of subsampled input images in advance. The accuracy and computation time of FR-PCA depends on the number of subsampling patterns required for generating the eigenspace. The final weight of FR-PCA dose not represent the complete occluded region as shown in Fig. 6, since the weights are selected from a set of subsamplings. For the purpose of comparison, we obtain the occlusion map by applying Eq. (11) to the reconstructed image as shown in Fig. 6. We compare the six face recognition algorithms such as the LBP-based face recognition algorithm with and without occluded-region detection (FR-PCA and FW-PCA) and the POC-based face recognition algorithms with and without occluded-region detection (FR-PCA and FW-PCA). We also evaluate three situations: face images with natural occlusion such as eyeglass and artificial occlusion such as the rectangular black region, where the block size is 32×32 and 64×64 pixels in the experiments.

Figs. 5, 7 and 8 show examples of the face image and the detected occlusion map for each situation. From these results, the occluded regions in the face image are correctly

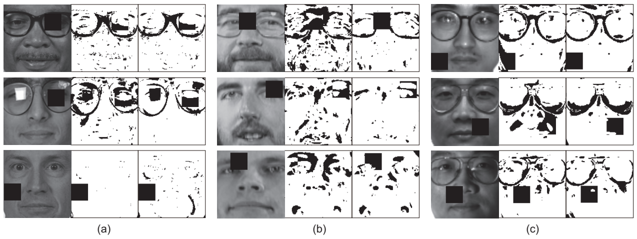

Figure 7. Examples of face images with artificial occlusion (32 × 32-pixel block): (a) FERET, (b) AT&T and (c) Yale (left: face image, center: occlusion map obtained by FR-PCA and right: occlusion map obtained by FW-PCA).

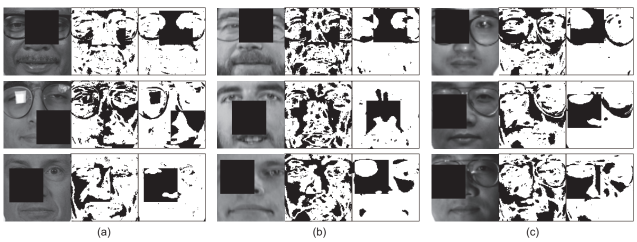

Figure 8. Examples of face images with artificial occlusion (64 × 64-pixel block): (a) FERET, (b) AT&T and (c) Yale (left: face image, center: occlusion map obtained by FR-PCA and right: occlusion map obtained by FW-PCA).

detected by using FW-PCA for both natural and artificial occlusions. On the other hand, FR-PCA cannot correctly detect the occluded region in the case of images with large occlusion as shown in Fig. 8.

Figs. 9, 10 and 11 show the ROC curves and EERs for each situation. In the case of face images with natural occlusion, "LBP with FW-PCA" and "POC with FW-PCA" observe 0.01%∼2%-improvement of EERs, while "LBP with FR-PCA" and "POC with FR-PCA" sometimes observe lower EERs than the original LBP and POC. Even though the occluded regions are small, the proposed framework can improve the performance of the face recognition algorithms. In the case of face images with the large artificial occlusion, "LBP with FW-PCA" and "POC with FW-PCA" observe 2∼12.8%-improvement of EERs, while "LBP with FR-PCA" and "POC with FR-PCA" observe 0.6∼9%-improvement of EERs. The performance of the face recognition algorithms are significantly improved by using the proposed framework.

To demonstrate the effectiveness of the proposed framework, we evaluate the performance using AR Face Database [12]. The AR Face Database include face images with different facial expressions, illumination conditions, and occlusions. Among 14 types of variations, we use the four types of face images: neutral expression, anger, wearing sun glasses and wearing scarf as shown in Fig. 12. The total number of images used in this experiment is 1,020. We use face images in the color FERET database as the training images, since the face images in AR Face Database are color images. We select 994 face images having no occlusion from the color FERET database to compute the eigen space $\mathbf{E}$. Note that occluded-region detection for color face images is the same for grayscale face images. All the parameters for face recognition algorithms are also the same for grayscale face images. Fig. 12 shows examples of occluded-region detection for the AR Face Database. The detection results of FW-PCA exhibit better results than FR-PCA. In this experiment, we randomly select 300 genuine and 1,000 impostor pairs similar to the above experiments. Fig. 13 shows the ROC curves and EERs for the AR Face Database. We observe 0.8∼4%-improvement of EERs using the proposed framework. As is observed in the above experiments, the use of the propose face recognition framework makes it possible to improve the performance of face recognition algorithms even for face images with/without occlusion.

5. Conclusion

This paper has proposed a novel framework of face recognition combined with the occluded-region detection method. The computation time of the occluded-region detection method using FW-PCA is about 100 msec. with Intel Core2 Duo (2.2GHz) and C++ implementation. Through a set of experiments using the public face image databases, the proposed framework has improved the performance of face recognition algorithms with a slight computational cost increase.

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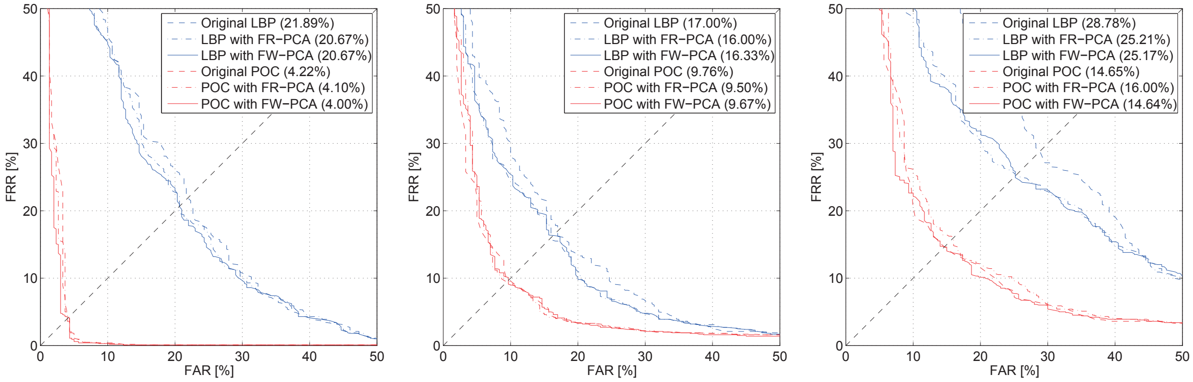
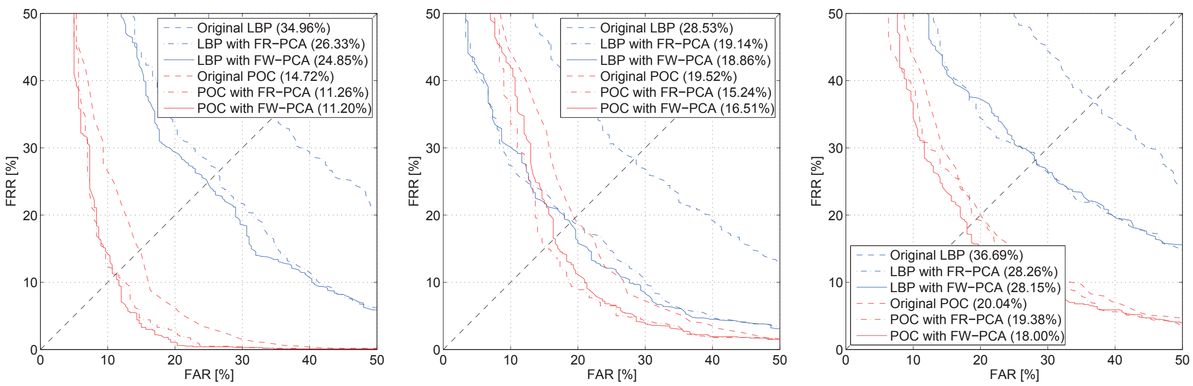


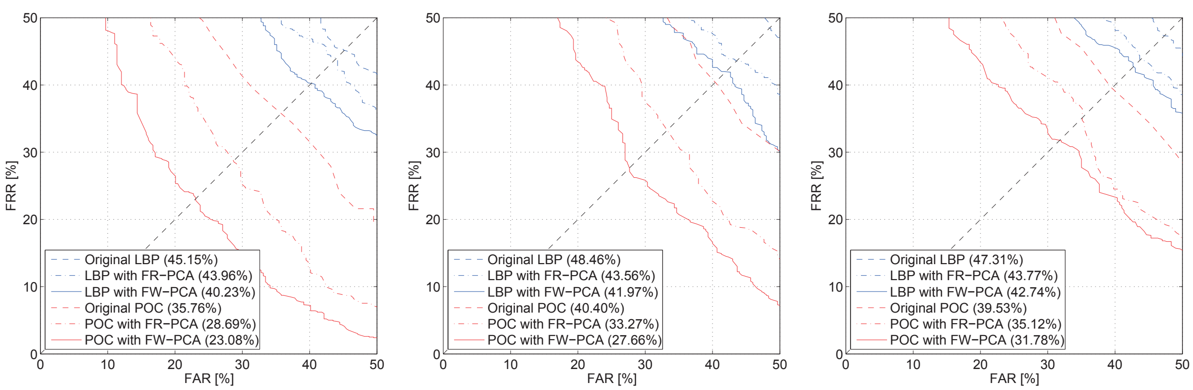
(a) (b) (c)

Figure 9. ROC curves and EERs using face images with natural occlusion: (a) FERET, (b) AT&T and (c) Yale.



(a) (b) (c)

Figure 10. ROC curves and EERs using face images with artificial occlusion (32×32-pixel block): (a) FERET, (b) AT&T and (c) Yale.



(a) (b) (c)

Figure 11. ROC curves and EERs using face images with artificial occlusion (64×64-pixel block): (a) FERET, (b) AT&T and (c) Yale.

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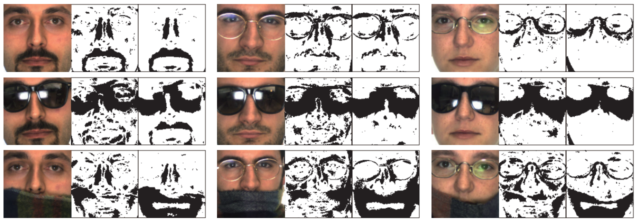

Figure 12. Examples of face images in AR database (left: face image, center: occlusion map obtained by FR-PCA and right: occlusion map obtained by FW-PCA).

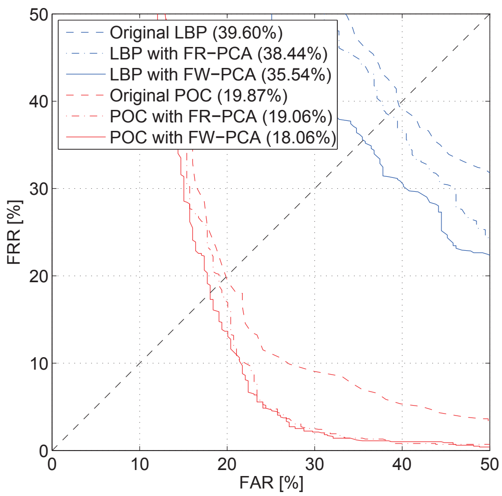

Figure 13. ROC curves and EERs for AR database.

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