A Multi-Level Supporting Scheme for Face Recognition under Partial Occlusions and Disguise

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Abstract. Face recognition has always been a challenging task in real-life surveillance videos, with partial occlusion being one of the key factors affecting the robustness of face recognition systems. Previous researches had approached the problem of face recognition with partial occlusions by dividing a face image into local patches, and training an independent classifier for each local patch. The final recognition result was then decided by integrating the results of all local patch classifiers. Such a local approach, however, ignored all the crucial distinguishing information presented in the global holistic faces. Instead of using only local patch classifiers, this paper presents a novel multi-level supporting scheme which incorporates patch classifiers at multiple levels, including both the global holistic face and local face patches at different levels. This supporting scheme employs a novel criteria-based class candidates selection process. This selection process preserves more class candidates for consideration as the final recognition results when there are conflicts between patch classifiers, while enables a fast decision making when most of the classifiers conclude to the same set of class candidates. All the patch classifiers will contribute their supports to each selected class candidate. The support of each classifier is defined as a simple distance-based likelihood ratio, which effectively enhances the effect of a "more-confident" classifier. The proposed supporting scheme is evaluated using the AR face database which contains faces with different facial expressions and face occlusions in real scenarios. Experimental results show that the proposed supporting scheme gives a high recognition rate, and outperforms other existing methods.

1 Introduction

Over the last decade, many mature algorithms have been developed for face recognition [1–5]. These algorithms often demonstrate promising results with high recognition rates on face image captured under ideal conditions such as frontal faces in passport photos. On the other hand, face recognition has always been a challenging problem in real-life surveillance videos where faces are always non-frontal, occluded, and in low resolutions. In particular, recognizing partially occluded or disguised faces is one of the key issues in enhancing the robustness of face recognition in real-life videos.

Currently, there are not many effective and efficient methods to handle face recognition with occlusions. Some common approaches to tackle the problem include face occlusion detection [6–9] and face division into local patches [9–13].

In [6], the occluded parts of a face were first detected according to the residual values, and a new face classifier was trained using the training samples with all the occluded parts being masked-out. Although this approach can effectively ignore the effect of the occluded parts, the recognition is extremely time-consuming since a new classifier has to be trained in run-time for every recognition. Fidler et al. [8] proposed a subspace recovering method for recovery the faces from occlusions. Their method reconstructed occluded parts of a face from the trained subspace before performing the recognition. The recognition correctness, however, is lowered due to the recovery errors, especially when the individual is not included in the training set. Jia and Martinez [14] suggested to use faces with occlusions as training samples to train a SVM classifier. This approach, however, is risky when the occlusion scenarios are not included in the training samples. Oh et al. [9] proposed a selective-LNMF classifier. Their method first divides and locates the occluded face patches, and re-projects the training samples to the selective-LNMF space, in which the LNMF bases belonging to the occluded face patches are excluded. The recognition stage of this method, however, can be very time-consuming when the face database grows large. Moreover, this method requires occlusion detection which was trained by partially occluded face samples, therefore, the method cannot solve the unseen occlusion case.

Instead of using occlusion detection and face recovery, Martinez [11] suggested to divide a face into 6 local patches, and weight each local patch according to a new training face set. This method then votes for the final recognition results according to the weightings of the local patches. Such a local face patches approach enhances the face recognition rate since it reduces the effect of the occluded parts in the recognition. However, the distinguishing information in the holistic face is also crucial in face recognition. If only local face patches are considered, the distinguishing information of the holistic face may be ignored. Kim et al. [13] suggested to combine local features and global holistic face information in the recognition. In their method, local-feature patches, including eyes, nose, month, are first located by local feature detectors. The final recognition is then decided by combining the local and global holistic face recognition results. They showed that their combination method outperforms both the global holistic approach as well as the local-patch approach. However, Kim et al. did not elaborate their method on occluded faces where the local face features might be occluded, and might not be easy to locate.

This paper proposes a novel multi-level supporting scheme which integrates the recognitions of global holistic face and multi-level local face patches. The main contributions of this paper include: 1) a novel multi-level supporting scheme which incorporates the decisions of multi-level patch classifiers, 2) a simple and effective distance-based likelihood ratio to enhance the weightings of "more-confident" patch classifiers, and 3) a criteria-based class candidates selection process which preserves more class candidates for consideration as the final recognition result when there are conflicts between patch classifiers. In summary, our method first divides a face image into local patches at different levels (figure 1). For each patch, including the global face image, a fisherface subspace classifier [15] is trained. In the testing stage, a testing face image is also divided into local patches as in the training stage. A multi-level supporting scheme is then applied to integrate the recognition results of the local patches. The scheme first selects potential class candidates according to the matching likelihood ratio between the testing and training faces. Each local patch classifier is then invited to give its support to these selected candidates. The final recognition result is decided according to the supports from all patch classifiers. The proposed scheme is efficient since it requires neither re-training nor re-projection of the training faces. The supporting scores contributed by the patch classifiers depend on a simple likelihood ratio which will be discussed in detail in Section 2. The proposed likelihood ratio measures how likely a testing patch belongs to the same class of a particular training face patch, and effectively decreases the effects of those patches with low confidence. Furthermore, the discriminant information on multi-level patches, including the global holistic face and local smaller patches, are all being considered and integrated. The proposed recognition is, therefore, more robust to partial face occlusions and facial expression changes. The proposed scheme is evaluated using the AR face database [16] which contains faces with different facial expressions and real occlusions. Experimental results shown in Section 3 shows the proposed scheme gives a high recognition rate, and generally outperforms existing state-of-the-art methods.

The paper is organized as follows. Section 2 describes in detail the proposed multi-level supporting face recognition scheme. Experimental results are then presented in Section 3, followed by the conclusions in Section 4.

2 Multi-Level Supporting Scheme

Face images are first divided into patches at different levels with slight overlapping (about one-eighth of the width/height) as shown in figure 1. In the experiments presented in this paper, each face image is divided into 2x2, 4x1, 1x4, 4x2 and 2x4 patches. Together with the original holistic 1x1 face image, there are in total 29 image patches. For each image patch, an independent classifier is trained as described in following sections.

2.1 Fisherface Subspace Classifiers

This section describes the subspace classifier for a single image patch. The classifiers for all the other image patches, including the global holistic face patch, are trained in the same way. For each face image patch, an independent fisherface classifier [15] is trained. Suppose there are N training face sample. An image patch of the i-th training sample is represented as a 1-D vector $\boldsymbol{x_i}$ in single grey channel. The vector $\boldsymbol{x_i}$ is projected to an eigenface subspace using principle component analysis (PCA) [15]:

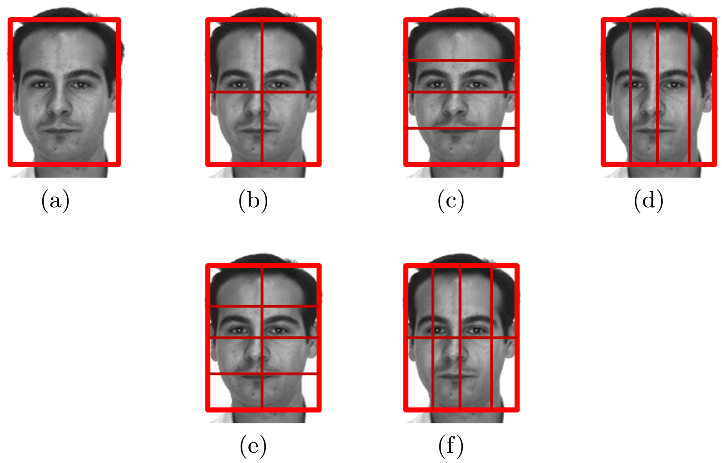

Fig. 1. Faces are divided into slightly overlapped patches at different levels: (a) manually cropped 1x1 holistic face, (b) 2x2 face patches, (c)(d) horizontal 4x1 and vertical 1x4 face patches, and (e)(f) horizontal 4x2 and vertical 2x4 face patches.

$$\hat{\boldsymbol{x}}_{\boldsymbol{i}} = \boldsymbol{U_K}^T(\boldsymbol{x_i} - \boldsymbol{m}) \tag{1}$$

where $\boldsymbol{m}$ is the mean vector of all training patch vectors $\boldsymbol{x}$, $\boldsymbol{U_K} = [\boldsymbol{u_1}, ...\boldsymbol{u_K}]$ is a matrix whose columns are the K eigenvectors with the largest eigenvalues of the scatter matrix $\boldsymbol{S_T}$:

$$\boldsymbol{S_T} = \sum_{i=1}^{N}(\boldsymbol{x_i} - \boldsymbol{m})(\boldsymbol{x_i} - \boldsymbol{m})^T \tag{2}$$

The set containing N faces in the fisherface subspace $\hat{\boldsymbol{Y}} = \{\hat{\boldsymbol{y}}_{\boldsymbol{1}}, ..., \hat{\boldsymbol{y}}_{\boldsymbol{N}}\}$ is then constructed by projecting the corresponding $\hat{\boldsymbol{x}}_{\boldsymbol{i}}$ to the fisherface subspace using linear discriminant analysis (LDA):

$$\hat{\boldsymbol{y}}_{\boldsymbol{i}} = \boldsymbol{W}^T(\hat{\boldsymbol{x}}_{\boldsymbol{i}} - \hat{\boldsymbol{m}}) \tag{3}$$

where $\hat{\boldsymbol{m}}$ is the mean vector of all training patch vectors $\hat{\boldsymbol{x}}$ in PCA subspace. $\boldsymbol{W}$ contains the bases of the LDA subspace which is calculated by maximizing the between-class scatter matrix $\boldsymbol{S_b}$ and minimizing the within-class scatter matrix $\boldsymbol{S_w}$. The optimal $\boldsymbol{W_{opt}}$ is defined as:

$$\boldsymbol{W_{opt}} = arg\ max\left|\frac{\boldsymbol{W}^T\boldsymbol{S_b}\boldsymbol{W}}{\boldsymbol{W}^T\boldsymbol{S_w}\boldsymbol{W}}\right| \tag{4}$$

$$\boldsymbol{S_b} = \sum_{i=1}^{C} n_i(\hat{\boldsymbol{m}}_{\boldsymbol{i}} - \hat{\boldsymbol{m}})(\hat{\boldsymbol{m}}_{\boldsymbol{i}} - \hat{\boldsymbol{m}})^T \tag{5}$$

$$\boldsymbol{S_w} = \sum_{i=1}^{C} \sum_{\boldsymbol{\hat{x}_k} \in \boldsymbol{\hat{X}_i}} (\boldsymbol{\hat{x}_k} - \boldsymbol{\hat{m}_i})(\boldsymbol{\hat{x}_k} - \boldsymbol{\hat{m}_i})^T \tag{6}$$

where C is the total number of training classes. n_i is the number of samples of the i-th class. $\boldsymbol{\hat{m}_i}$ and $\boldsymbol{\hat{m}}$ are the mean of the i-th class and the mean of all PCA samples respectively, and $\boldsymbol{\hat{X}_i} = \{\boldsymbol{\hat{x}_k}\}$ contains all PCA samples in the i-th class. As suggested in [1], this paper directly calculates the optimal $\boldsymbol{W_{opt}} = [\boldsymbol{w_1}, ...\boldsymbol{w_{\hat{K}}}]$ as the first $\hat{K}$ eigenvectors of $S_w^{-1} S_b$ with the largest eigenvalues.

2.2 Matching Likelihood Ratio

During the training stage, the mean μ^{intra} and variance ν^{intra} of the intra-class distances are calculated as:

$$\mu^{intra} = \frac{1}{N^{intra}} \sum_{c_k=1}^{C} \sum_{\boldsymbol{\hat{y}_i} \in \boldsymbol{\hat{Y}_{c_k}}} \sum_{\boldsymbol{\hat{y}_j} \in \boldsymbol{\hat{Y}_{c_k}}}^{i<j} d_{i,j} \tag{7}$$

$$\nu^{intra} = \frac{1}{N^{intra}} \sum_{c_k=1}^{C} \sum_{\boldsymbol{\hat{y}_i} \in \boldsymbol{\hat{Y}_{c_k}}} \sum_{\boldsymbol{\hat{y}_j} \in \boldsymbol{\hat{Y}_{c_k}}}^{i<j} (d_{i,j} - \mu^{intra})^2 \tag{8}$$

where C is the total number of classes, $d_{i,j} = [(\boldsymbol{\hat{y}}_i - \boldsymbol{\hat{y}}_j)^T \Sigma^{-1} (\boldsymbol{\hat{y}}_i - \boldsymbol{\hat{y}}_j)]^{1/2}$ is the Mahalanobis distance between $\boldsymbol{\hat{y}}_i$ and $\boldsymbol{\hat{y}}_j$, $\boldsymbol{\hat{Y}_c} = \{\boldsymbol{\hat{y}_i} : \boldsymbol{\hat{y}_i} \in class\ c\}$ contains all the faces of class c in fisherface subspace, and N^{intra} is the total number of the intra-class combinations.

Similarly, the mean μ^{inter} and variance ν^{inter} of inter-class distances are defined as:

$$\mu^{inter} = \frac{1}{N^{inter}} \sum_{c_k=1}^{C} \sum_{\boldsymbol{\hat{y}_i} \in \boldsymbol{\hat{Y}_{c_k}}} \sum_{\boldsymbol{\hat{y}_j} \in \boldsymbol{\hat{Y}_{c_t}}}^{c_k < c_t \leq c_N} d_{i,j} \tag{9}$$

$$\nu^{inter} = \frac{1}{N^{inter}} \sum_{c_k=1}^{C} \sum_{\boldsymbol{\hat{y}_i} \in \boldsymbol{\hat{Y}_{c_k}}} \sum_{\boldsymbol{\hat{y}_j} \in \boldsymbol{\hat{Y}_{c_t}}}^{c_k < c_t \leq c_N} (d_{i,j} - \mu^{inter})^2 \tag{10}$$

where N^{inter} is the number of inter-class combinations.

With the means and variances of intra- and inter-class distances, the matching likelihood ratio $L_{i,j}$ is defined based on the distance $d_{i,j}$ between $\boldsymbol{\hat{y}}_i$ and $\boldsymbol{\hat{y}}_j$:

$$L_{i,j} = \frac{p^{intra}(d_{i,j})}{p^{inter}(d_{i,j})} \tag{11}$$

where $p^{intra}(d)$ and $p^{inter}(d)$ are the probability density functions (pdf) of intra- and inter-class distances respectively. $p^{intra}(d)$ and $p^{inter}(d)$ are implemented as a slightly modified Gaussian functions:

$$p^{intra}(d) = \frac{1}{\sqrt{2\pi\nu^{intra}}} e^{\frac{-(t^{intra}-\mu^{intra})^2}{2\nu}} \tag{12}$$

$$p^{inter}(d) = \frac{1}{\sqrt{2\pi\nu^{inter}}} e^{\frac{-(t^{inter}-\mu^{inter})^2}{2\nu}} \tag{13}$$

where μ^{intra} and ν^{intra} are intra-class distance mean and variance specified in (7) and (8) respectively, and μ^{inter} and ν^{inter} are inter-class distance mean and variance specified in (9) and (10) respectively. $t^{intra} = max(d, \mu^{intra})$ and $t^{inter} = min(d, \mu^{inter})$ are the modified distance terms for p^{intra} and p^{inter} respectively. As illustrated in figure 2, these two terms ensure the likelihood ratio L obeys the similarity rule. The distance d is assumed to give equal intra-class probability $p^{intra}(d)$ when $d < \mu^{intra}$, and give equal inter-class probability $p^{inter}(d)$ when $d > \mu^{inter}$.

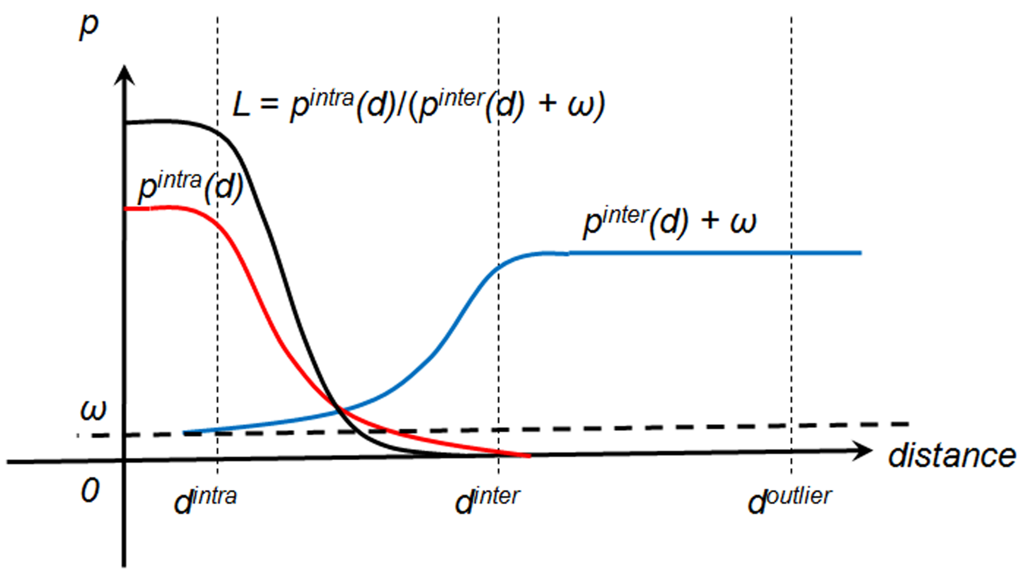

Fig. 2. An illustration of the likelihood functions. The likelihood L is large when the distance belongs to intra-class distance (d^{intra}), and L decreases dramatically when the distance approaches the inter-class distance (d^{inter}) or the outlier distance ($d^{outlier}$).

Given the distance $d_{i,j}$, $p^{intra}(d_{i,j})$ measures how likely $\hat{\boldsymbol{y}}_i$ and $\hat{\boldsymbol{y}}_j$ belong to the same class, whereas $p^{inter}(d_{i,j})$ measures how likely these two faces belong to different classes. Therefore, the larger the likelihood ratio defined in (11), the more likely the faces belong to the same class. Furthermore, an ω term is also added in the denominator of (11) to fix the likelihood ratio L:

$$L_{i,j} = \frac{p^{intra}(d_{i,j})}{p^{inter}(d_{i,j}) + \omega} \tag{14}$$

This ω term is used to prevent the likelihood ratio $L_{i,j}$ of a particular patch classifier becoming too large when the corresponding distance $d_{i,j}$ is too small, and therefore, preventing such patch classifier dominating the final recognition result. As illustrated in figure 2, this formulation effectively enhances the likelihood ratio when a face patch is matching with an intra-class patch, and the ratio decreases dramatically when the face patch is matching with an inter-class patch or an outlier/occluded patch with reasonable assumption that $d^{intra} < d^{inter} < d^{outlier}$.

2.3 Class Candidates Selection

In the recognition stage, a testing face image is divided into patches in the same way as the training images shown in figure 1. Each patch then undergoes classification matchings with the corresponding patches of the training samples. For a patch classifier p, the matching likelihood ratio $L_{p,c,k}$ of the k-th training sample in class c is calculated as in (14). After that, a set of class candidates is selected based on a criteria-based majority voting. The class candidate set is constructed in two stages: 1) First, a set of class votes $\boldsymbol{V} = \{v_c\}$ is constructed by a criteria-voting, where v_c is the number of votes for class c. Each patch classifier p votes for c whenever there exists a training sample k belonging to c with a matching likelihood ratio $L_{p,c,k}$ larger than a pre-defined threshold τ. 2) The class candidate set $\hat{\boldsymbol{C}}$ is then constructed as:

$$\hat{\boldsymbol{C}} = \{c : v_c \ > \ \lambda\} \tag{15}$$

where λ is a loose-to-fine variable threshold. In the experiment, τ is set to 0.9, and λ is set to $M/2$ at first where M is the total number of patch classifiers. λ is then iteratively decreased by halving its value at each step until $\hat{\boldsymbol{C}} \neq \emptyset$. This variable λ preserves more class candidates when there is more conflicts between classifiers. On the other hand, a faster decision can be made when majority of the classifiers are supporting to certain classes.

2.4 Multi-Level Supporting

For each potential class candidate selected, the supporting is initiated by asking the support $s_{p,c}$ for the corresponding class c from each patch classifier p. The support from the p-th patch classifier is simply defined as the maximum likelihood ratio of the samples belonging to class c:

$$s_{p,c} = max.L_{p,c,k} \ for \ all \ sample \ k \ \in \ class \ c \tag{16}$$

The final support S_c for a class c is then defined as the weighted sum of $s_{p,c}$:

$$S_c = \sum \alpha_p s_{p,c} \tag{17}$$

where α_p is the corresponding weighting of the patch classifier p. In the experiment, the weightings α_p of all patch classifiers are set to equal-value, and so the supports from all classifiers are equally weighted.

3 Experimental Results

The proposed method is evaluated using the AR database [16] with real occlusion scenarios and different facial expressions. The database contains 134 individuals including 76 males and 58 females. For each individual, there are several face categories in which faces are in different facial expressions and occlusions (figures 3). In the experiments, the face categories normal (figure 3(a)(g)), smile (figure 3(b)(h)) and angry (figure 3(c)(i)) are used for training. The face categories scream (figure 3(d)(j)), sun-glasses (figure 3(e)(k)) and scarf (figure 3(f)(l)) are used for testing the proposed scheme with real occlusions and in different facial expressions. In addition, the normal face category is made synthetically occluded by random masks (figure 4). This set is used for evaluating the proposed scheme under synthetic occlusions. All the faces for training and testing are manually cropped, aligned by eyes, and resized to 48x64.

3.1 Synthetic Occlusions

The faces in the normal category were occluded by synthetic black masks at random positions as shown in figure 4. The dimensions of these black boxes were also randomly selected with approximate size of 16%, 25%, 36%, 49% and 64% of the whole face image respectively. The occluded face images were then used to evaluate the proposed method.

Table 1. Face recognition results with synthetic occlusion masks

	Recognition Rate (%)				
	16% Occl.	25% Occl.	36% Occl.	49% Occl.	64% Occl.
Prop. ML-Support	**100.0**	**100.00**	**98.51**	**90.30**	**72.39**
Local-Vote(4x2)	**100.0**	98.51	84.33	67.91	53.73
ML-Vote	**100.0**	97.01	76.12	56.72	38.06
Fisher [15]	88.06	56.72	26.87	14.93	7.46

Table 1 shows the recognition results of the proposed multi-level supporting scheme (Prop. ML-Support). The recognition results of fisherface (Fisher) [15], majority voting of local patches (Local-Vote) and majority voting of patches at all levels (ML-Vote) are also listed in the table. Note that the testing samples are

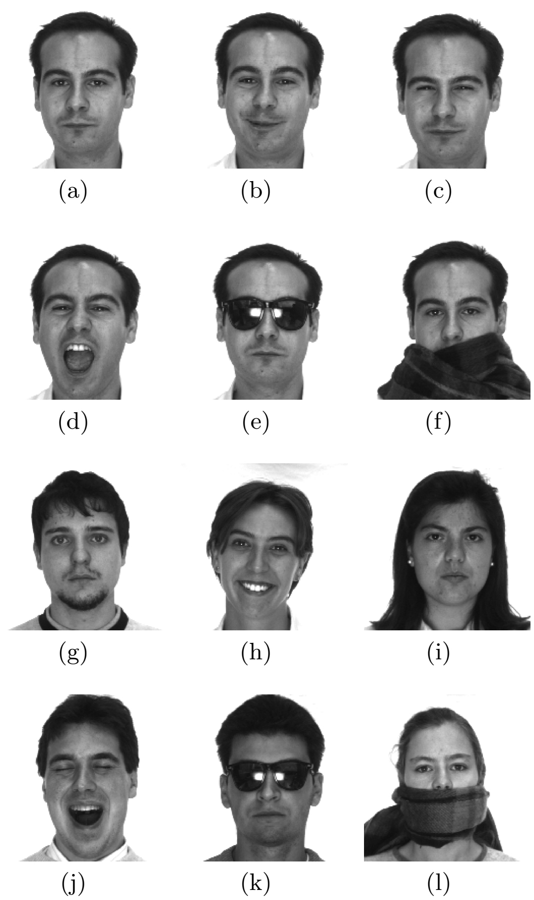

Fig. 3. Face samples in the AR database which contains faces with different facial expressions and occlusion scenarios. The first two rows show the faces of a particular individual in different face categories. The next two rows show other individuals' faces which belong to the corresponding categories as the first two rows. The face categories include: (a)(g) normal, (b)(h) smile, (c)(i) angry, (d)(j) scream, (e)(k) sun-glasses and (f)(l) scarf.

Fig. 4. Cropped faces in category normal with synthetic occlusions of about: (a)(f) 16%, (b)(g) 25%, (c)(h) 36%, (d)(i)49% and (e)(j)64%.

selected from one of the face categories used for training with synthetic occlusions added. The Local-Vote approach takes the advantages under heavy occlusions since the non-occluded patches should match exactly with the corresponding training patches, and thus outperforms the ML-Vote approach whose results are affected by the patches in the higher levels under heavy occlusions. The proposed supporting scheme, on the other hand, is able to enhance the leverage of the non-occluded patch classifiers, and incorporate those "more-confident" patches at different levels. The results show that the proposed scheme outperforms the fisherface and other majority voting approaches, and is able to enhance the recognition rate up to nearly 90% and 72% under extremely heavy occlusions of about 49% and 64%, respectively.

3.2 Facial Expression Changes and Real Occlusions

Table 2. Face recognition results with real occlusion

	Recognition Rate (%)		
	Scream	Sun-glasses	Scarf
Prop. ML-Support	**92.54**	**92.54**	**93.28**
Local-Vote(4x2)	88.81	82.09	92.54
ML-Vote	90.03	85.07	89.55
Fisher [15]	67.16	59.70	32.84
Sub-Recovery [8]	87.00	84.00	93.00
Occl-SVM [14]	–	57.0	57.0
sLNMF [9]	44	90	92

Table 2 lists the recognition rates of the proposed Multi-Level supporting scheme (Prop. ML-Support) with real occlusion scenarios (figure 3 (e)(k) sunglasses and (g)(l) scarf) and different facial expressions (figure 3 (d)(j) scream). Similar to the synthetic occlusion experiments, the recognition results of fisherface (Fisher) [15], majority voting of local patches (Local-Vote) and majority voting of patches at all levels (ML-Vote) are also listed in the table. Furthermore, the recognition rates presented in [8] (Sub-Recovery), [14] (Occl-SVM) and [9] (sLNMF) are also included for comparisons. The results show that the proposed supporting scheme outperforms the traditional holistic and majority voting approaches under real occlusions and facial expression changes.

The performance of the proposed scheme is also generally better than the previous methods [8, 14, 9]. Unlike sLNMF [9], the proposed scheme not only tackles recognition under partial occlusions, but also tolerates facial expression changes. The recognition rate of the proposed scheme is much better than Jia and Martinez's method (Occl-SVM) [14]. Note that Jia and Martinez used the occluded faces (sun-glasses and scarf categories) as training samples, and another set of sun-glasses and scarf face categories, which were taken separately, is used as testing samples. It is expected that the results of the proposed supporting scheme will be even better if such occluded face sets are also used for the training. The proposed scheme demonstrates slightly better results than Fidler et al.'s recovery approach [8] for the scarf samples, and outperforms their method for the scream and sun-glasses samples. Note that the proposed scheme does not require complicated iterative face recovery process, and therefore, is more efficient.

4 Conclusions

This paper introduces a novel multi-level supporting scheme for face recognition under partial occlusions and disguise. This scheme effectively incorporates the face discriminant information at multiple face levels with the proposed matching likelihood ratio for each face patch. This likelihood ratio is designed to enhance the effect of well-matched patches while making the effect of bad-matched patches negligible. This approach allows the best-matched patch classifiers to give more contributions since they are the "most-confident" classifiers. In addition, the candidate selection scheme also allows more individual candidates to be considered at the initial recognition stage when there exist conflicting classifiers, and thus enhancing the final supporting results. Experimental results show the proposed method provides a more robust and effective face recognition system, especially when the faces are under occlusions, and it can tolerate different facial expressions. The results also demonstrate the proposed method outperforms the previous methods under such scenarios.

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