# Occlusion Invariant Face Recognition Using Selective Lnmf Basis Images

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**Abstract.** In this paper, we propose a novel occlusion invariant face recognition algorithm based on Selective Local Nonnegative Matrix Factorization (S-LNMF) technique. The proposed algorithm is composed of two phases; the occlusion detection phase and the selective LNMF-based recognition phase. We use local approach to effectively detect partial occlusion in the input face image. A face image is first divided into a finite number of disjointed local patches, and then each patch is represented by PCA (Principal Component Analysis), obtained by corresponding occlusion-free patches of training images. And 1-NN threshold classifier was used for occlusion detection for each patch in the corresponding PCA space. In the recognition phase, by employing the LNMF-based face representation, we exclusively use the LNMF bases of occlusion-free image patches for face recognition. Euclidean nearest neighbor rule is applied for the matching. Experimental results demonstrate that the proposed local patch-based occlusion detection technique and S-LNMF-based recognition algorithm works well and the performance is superior to other conventional approaches.

## 1 Introduction

One of the most important goals of computer vision is to achieve visual recognition ability comparable to that of human [11],[12],[13]. And among many recognition subjects, the face recognition problem has been researched intensively during last few decades, due to its great potential in the various practical applications such as HCI Human Computer Interface), intelligent robot, surveillance, and so on. And, if the face recognition is diverged further, obvious problem of occlusion by other objects or apparels such as sunglasses or scarves becomes eminent. Thus a robust algorithm for occluded faces is required for real applications. So far, several approaches dealing with occlusion have been proposed in the literature. A. Leonardis and H. Bischof [1],[2] proposed a robust PCA approach that could estimate the coefficients of eigenimages from partially degraded images. This approach presented successful reconstruction of partially occluded images, however the performance was usually de-

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pended on training set. S. Z. Li et al. proposed a novel method, called local non-negative matrix factorization (LNMF) [3], for learning spatially localized, parts-based subspace representation of visual patterns. In addition to the non-negativity constraint in the standard NMF, the prescribed objective function imposed localization constraints, [4]. Experimental results compared LNMF with the NMF and PCA methods for occluded face recognition, where the advantages of LNMF were demonstrated. A. M. Martinez [5] described a probabilistic approach that is able to compensate for imprecisely localized, partially occluded, and expression-variant faces when only single training sample per class was available to the system.

In this paper, we present a novel face recognition algorithm robust to occlusion using S-LNMF technique. The proposed algorithm is based on a local approach where face images are divided into a finite number of disjointed local patches. But, unlike previous approaches, we perform occlusion detection explicitly. The occluded regions in the face images are detected by 1-NN classifier. Afterwards, the recognition process is performed over selected LNMF bases of occlusion-free patches. We evaluate our algorithm on the occlusion subset of the AR database [6], and demonstrate that the proposed algorithm has superior performance than previous face recognition schemes.

## 2 Occlusion Detection

The proposed face recognition algorithm is based on selected LNMF subspace matching. Note that since each LNMF basis image exhibits high localization characteristics in spatial domain, local occlusion affects only the coefficients of the corresponding bases, so that the error becomes local and not global. So, by using the LNMF bases for occlusion-free regions exclusively, we can achieve robust matching for occlusion. However, in order to select relevant local bases, we need to determine the occluded regions in a face image in advance. In this section we propose an occlusion detection algorithm based on one class classifier in PCA space.

### 2.1 Local Subdivision of a Face Image

Partial occlusions in face images usually occurs when subjects wear adornments like sunglass or scarf, or when faces are covered by other objects such as hands, cup and so on. In order to detect the locally occluded regions in a face image, we first divide the image into a finite number of local disjoint patches as in Fig. 1, and then examine each patch individually [5].

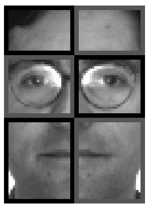


**Fig. 1.** Local subdivision of a face

### 2.2 Local Occlusion Detection in PCA

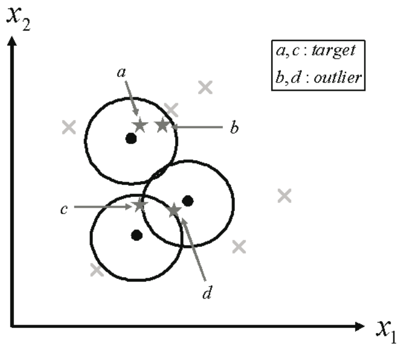
Occlusion detection of a given face image is accomplished for each local patch independently by employing pattern classification framework. Note that each local patch is still high dimensional data that are computationally infeasible. So we deal with each patch image in a low dimensional subspace after dimension reduction using PCA (Principal Component Analysis) [10],[14],[15],[16],[17].

6 PCA subspaces corresponding to 6 local patches of occlusion-free faces are trained by normal face images. When a test face image is given, it is divided into 6 local patches as shown in Fig. 1, and then each patch, $k=1,2,\ldots 6$, are projected onto the corresponding eigenspace, producing the PCA coefficients. So, the occlusion detection for each patch is accomplished by comparing the coefficient vectors of occlusion-free images with that of the test image in the corresponding eigenspace.

### 2.3 Supervised l-Nearest Neighbor Threshold Classfiers

To distinguish normal data from occluded ones in eigenspace, we need a proper classifier. Occlusion detection problem can be seen as a type of one class classification problem [7],[8]. That is, the goal of one class classification is to accurately describe one class of objects, disregarding a wide range of other objects that are not of interest.

In general, the performances of conventional classifiers such as k-NN and 1-NN classifier are highly dependent on the number of training samples. However, sufficient training samples are not always provided. To improve the classification performance when the number of training data is limited, we introduce a supervised 1-NN threshold classifier that employs absolute distance between samples contrast to the relative distance of k-NN classifier and 1-NN distance classifier. With a reasonable threshold value, making hyperspheres of target class data can reduce the classifier's dependency upon the number of training data. Fig. 2 (a) shows the concept of the proposed classifier. The radius of hypersphere is represented as the circles and outlier class data are illustrated as X. When an unknown input test data is entered, the nearest neighbor among training data is found. If the nearest neighbor is an outlier class data, the test data is labeled as outlier class data. If the nearest neighbor is a target class data, distance between the input data and the nearest one is measured.




```
/* Supervised 1-NN threshold classifier */

Find the nearest neighbor of a test data.
If the nearest neighbor is an outlier,
    test data is assigned to the outlier class .
Else
    if distance < threshold,
        test data is assigned to the target class.
    else
        test data is assigned to the outlier class.
```

(a) (b)

**Fig. 2.** Supervised 1-NN threshold classifier

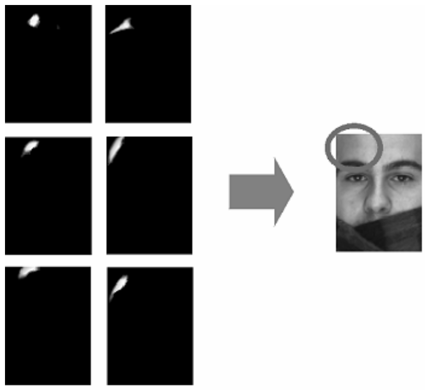


**Fig. 3.** Example of LNMF bases

If the distance is smaller than a threshold value, which is the hypersphere radius, the test data is labeled as target class data, or else outlier class data. The algorithm is summarized as in Fig.3 (b). According to this algorithm, data *a* and *c* are classified correctly as the target class since the nearest neighbor is the target class data and they are within the hypersphere. And although data *b* is located in the hypersphere, it is correctly classified as an outlier since its nearest neighbor is the outlier.

## 3 Face Recognition Using Selective LNMF Basis Images

After detecting occluded regions by the methods mentioned in the previous section, LNMF based matching technique is applied for recognition. Since the occluded regions are already identified, LNMF bases corresponding to only occlusion-free regions are to be integrated.

### 3.1 LNMF Basis Selection

Unlike PCA which exhibits holistic features of an image, LNMF can learn spatially localized, parts-based subspace representation [3]. Moreover, the significance between LNMF bases is non-hierarchic. Since the maximum number of LNMF bases that can be learned is infinite, we can initiate the number of bases. Note that LNMF bases are spatially localized; some are corresponding to occluded regions and the others are corresponding to occlusion-free regions. If we choose to indiscriminately use all the bases for face recognition, the bases corresponding to occluded regions will degrade the recognition performance. Therefore it is natural to employ the bases corresponding to the occlusion-free regions selectively. In Fig. 3, 6 images on left show an example of LNMF basis images corresponding to the occlusion-free upper left region of a face. These bases are nearly independent to the lower occluded part by scarf, and thus can be used to reconstruct the local region correctly. Similarly, other bases, not located at the occluded region can contribute to the recognition.

In order to detect bases for occluded region, let us define a measure for occluded energy per each basis as follows.

$$E^{i}_{Occlusion} = \frac{\sum_{x,y \in W} I_i^2(x,y)}{\sum_{x=1}^{C} \sum_{y=1}^{R} I_i^2(x,y)}, \quad i = 1,2,\ldots,N, \tag{1}$$

where $C \times R$ is the image size, $I_i(x, y)$ is the value of the $i_{th}$ LNMF basis at $x$ column and $y$ row, $W$ is the detected occluded region, and $N$ is the number of bases.

### 3.2 Face Recognition in LNMF Subspace

Face recognition is performed in the LNMF subspace spanned by occlusion-free bases. Since LNMF bases set is not orthonormal like PCA bases set, in order to calculate the LNMF coefficients of an input image, we use pseudo inverse of the selected occlusion-free LNMF bases matrix. Let $\mathbf{B} = [\mathbf{b}_1\ \mathbf{b}_2 \cdots \mathbf{b}_N]$ be the original LNMF bases set. For a given test face $\mathbf{y}$, we can determine the occlusion-free basis set associated with it, and denote it as $\mathbf{W} = [\mathbf{w}_1\ \mathbf{w}_2 \cdots \mathbf{w}_M]\ (\mathbf{W} \subset \mathbf{B}, M \le N)$. Then the selected coefficient vector $\mathbf{h}$ of $\mathbf{y}$ can be obtained by

$$\mathbf{h} = \mathbf{W}^{+}\mathbf{y}, \tag{2}$$

where $\mathbf{W}^{+}$ is the pseudo inverse of $\mathbf{W}$. Similarly, each training face image $\mathbf{x}_i\ (i = 1,2,\cdots,K)$, where $K$ is the total number of training faces, is projected into the same selected occlusion-free LNMF subspace with coefficient vector $\mathbf{g}_i\ (i = 1,2,\cdots,K)$.

$$\mathbf{g}_i = \mathbf{W}^{+}\mathbf{x}_i, \quad i = 1,2,\cdots,K. \tag{3}$$

Then, the recognition is performed by finding the closest training face in the feature space as follows.

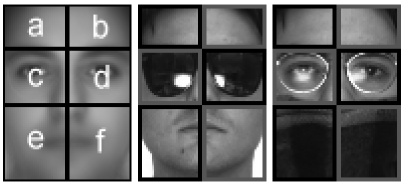
$$\arg\min_i \| \mathbf{g}_i - \mathbf{h} \|, \quad i = 1,2,\cdots,K. \tag{4}$$

Since only selected basis images are used in the proposed algorithm, unlike original face recognition technique using LNMF [3], the number of basis images used for recognition changes according to the result of the occlusion detection.

## 4 Experimental Results

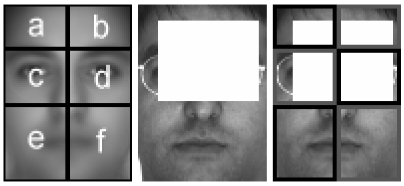
### 4.1 The AR-Face Database

We used the AR face database for our test [6]. For illustration, normal and partially occluded images by sunglass and scarf are shown in Fig. 4 (b) and (c). Localization and normalization for each face images are performed by aligning eye positions, removing background and warping, so that each face became a 64 x 88 array of 256 grayscale values. We performed experiments with 56 men and 44 women selected at random. We use normal (occlusion free), sunglass, and scarf images totaling 300 images. Among them, 100 normal images are used for LNMF bases learning. For the supervised classifiers for occlusion detection, 50 sunglass images and 50 scarf images are used as outlier class data in the training phase. The rest 50 sunglass and 50 scarf images are used for the test of face recognition.




(a) (b) (c)

**Fig. 4.** Example of partially occluded faces




(a) (b) (c)

**Fig. 5.** Synthetic occlusion patterns

### 4.2 Occlusion Detection Results

#### 4.2.1 The Performance Comparisons of the Classifiers

We quantitatively evaluated the performances of the occlusion detection schemes. Occluded regions are detected in the eigenspace, the feature space trained by PCA. Each training normal face image is divided into 6 disjoint patches as shown in Fig. 4 (a), and the corresponding 6 eigenspaces are learned. Fig. 4 (b) and (c) show examples of test occluded faces, in which patches (**c**, **d**) and (**e**, **f**) are occluded, respectively. Considering LNMF bases selection after occlusion detection, discarding the normal data labeled as the occluded data may reduce the information that can be used for recognition to some extent. However, using the occluded data labeled as the normal data in the recognition phase lowers the performance seriously since it delivers disturbed information. Thus, as a measurement compared with the performances of the classifiers, we evaluated the false alarm rate when the detection rate is 100% (false rejection rate is 0%).

The detection results on test images are shown in Table 1. In case of $k$-NN classifier the performance when $k$ = 3 is worse than when $k$ = 1. This shows that the finding numerous nearest neighbors lowers the detection performance. The supervised 1-NN threshold classifier and the $k$-NN with $k$ = 1 gave the best results in this test. Now, these two classifiers were tested on test images with synthetic occlusion pattern that were quite different from the trained outlier patterns as shown in Fig. 5 (b) and (c). We have examined the occluded patches a, b, c, and d. Since no false alarm can occur in this test, detection rates were calculated and summarized in the Table 2. Note that the supervised 1-NN threshold classifier still gave robust performance, while the $k$-NN classifier didn't work at all under this circumstance. Based on the above results, we chose the supervised 1-NN threshold classifier as the occlusion detector for our face recognition system.

**Table 1.** The performance comparison of the classifiers on real occlusion

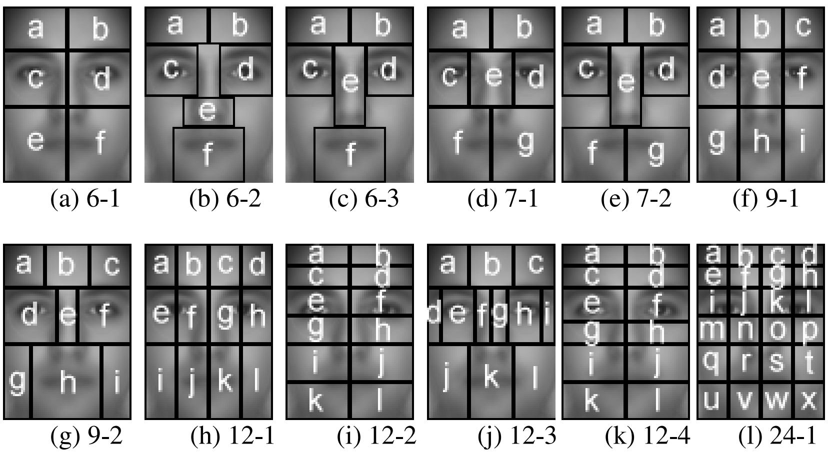
| Classifier | Detection Rate / False Alarm Rate (%) | | | | Average FAR (%) |
|---|---|---|---|---|---|
| | **c** | **d** | **e** | **f** | |
| *k*-NN (k=3) | 100/0 | 100/0 | 100/4 | 100/2 | 1.5 |
| k-NN (k=1) | 100/0 | 100/0 | 100/0 | 100/0 | 0 |
| Supervised 1-NN threshold | 100/0 | 100/0 | 100/0 | 100/0 | 0 |

### 4.2.2 Subdivision of Face Image

Proposed partial occlusion detection and face recognition algorithm are developed based on local patches of a face image. Thus, different division methods may result in different performances on both occlusion detection and recognition. In this section, we examine the optimal subdivision method of face images in an empirical sense. Fig. 6 shows 12 possible subdivision layouts that we have considered in this experiment. The supervised 1-NN threshold classifier was used for the comparison of the occlusion detection performances. And the false alarm rate with 100% detection rate for each subdivision method was calculated for the performance evaluation. Table 3 shows the results of the test. From these results, we concluded that the method 6-1 is optimal.

**Table 2.** The performance comparison of classifiers on synthetic occlusion

| Classifier | Detection Rate / False Alarm Rate (%) | | | | Average DR (%) |
|---|---|---|---|---|---|
| | **a** | **b** | **c** | **d** | |
| *k*-NN (*k*=1) | 0/- | 0/- | 0/- | 0/- | 0 |
| Supervised 1-NN threshold | 100/- | 100/- | 100/- | 100/- | 100 |



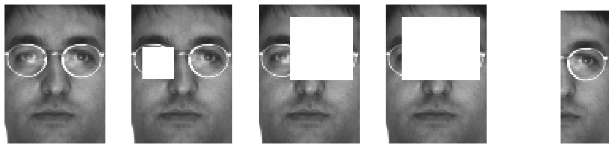
(a) 6-1 (b) 6-2 (c) 6-3 (d) 7-1 (e) 7-2 (f) 9-1

(g) 9-2 (h) 12-1 (i) 12-2 (j) 12-3 (k) 12-4 (l) 24-1

**Fig. 6.** Subdivision methods

**Table 3.** Detection performance of subdivision method

| Method | **6-1** | **6-2** | **6-3** | **7-1** | **7-2** | **9-1** |
|---|---|---|---|---|---|---|
| Average FAR (%) | 0 | 32.5 | 15.5 | 1.2 | 0.4 | 14.3 |
| Method | **9-2** | **12-1** | **12-2** | **12-3** | **12-4** | **24-1** |
| Average FAR (%) | 9.7 | 3.8 | 7.0 | 16.7 | 7.0 | 16.3 |



(a) (b) (c) (d) (e)

**Fig. 7.** Examples of Synthetically occluded test images

## 4.3 Face Recognition Results

### 4.3.1 LNMF Bases

We have trained 100 occlusion-free training face images in the AR database. The bases for occluded regions are detected by the equation (1) with a threshold of 0.1, which means that any basis, whose energy in an occluded region is greater than 10% of the total energy, will not be used for matching.

### 4.3.2 Experiments on Synthetic Occlusions

First, we tested our S-LNMF based recognition algorithm on synthetically occluded images as shown in Figs. 8 (b)-(e). Occlusion-free images as in Fig. 7 (a) were used for the training. Some conventional algorithms including PCA [10], LNMF [3] and R-PCA [1],[2] were also tested for the comparative performance evaluation. The recognition rate, defined as the percentage of correctly recognized faces, is used as the performance measure. Table 4 show the recognition results. The recognition rate of the proposed algorithm was obtained when the number of bases was 100. Experimental results show that the proposed algorithm achieved the highest recognition rate. Although R-PCA gave slightly better results than PCA and LNMF, the performance decreased drastically as the size of the occluded region became larger.

### 4.3.3 Experiments on Real Occlusions

We have tested our algorithm on real face images occluded by sunglass and scarf in AR database. All 135 people (76 men and 59 women) in the AR face database were used. Among these, all 135 normal face images and 70 occluded face images (35 sunglass images and 35 scarf images of 20 men and 15 women) were used for the training the target class and the outlier class, respectively. The remaining 100 sunglass images and 100 scarf images were used for probes and all the normal frontal faces were used for the gallery.

**Table 4.** Recognition rate (%) on synthetic occlusions

| | (a) | (b) | (c) | (d) | (e) |
|---|---|---|---|---|---|
| PCA | 100 | 100 | 24 | 8 | 6 |
| LNMF | 100 | 96 | 28 | 10 | 4 |
| R-PCA | 100 | 100 | 46 | 24 | 6 |
| **S-LNMF** | **100** | **100** | **100** | **100** | **100** |

**Table 5.** Recognition rate (%) on real occlusions

| **Algorithm** | **smile** | **scream** | **sunglass** | **scarf** |
|---|---|---|---|---|
| PCA | 94 | 44 | 40 | 14 |
| LNMF | 95 | 44 | 46 | 14 |
| R-PCA | 94 | 80 | 50 | 16 |
| AMM | 96 | 56 | 80 | 82 |
| **S-LNMF** | **95** | **44** | **90** | **92** |

Note that if there is no occlusion in a test face, then the algorithm becomes the very original LNMF-based recognition scheme, in which whole LNMF bases are integrated for matching, and the recognition performance of our algorithm will be the same as the original LNMF's [3]. Thus, in this paper, we investigate the performance of our algorithm on the occluded face images exclusively. Unlike the syntactic occlusion test where the occlusion-free parts of the gallery and the corresponding test images are exactly the same, in this case, those parts may differ since they are taken in different conditions. We found empirically that the optimal number of bases could be chosen from 200 to 400. The performances of PCA, LNMF, R-PCA and AMM (Martinez's algorithm [5]) were also evaluated and compared to that of the proposed algorithm, and the results are summarized in Table 5. The recognition rate of the proposed algorithm was obtained when the number of bases was 200.

From these results, we can conclude that our algorithm is more robust than other algorithms including AMM. AMM gave relatively better results than PCA, LNMF and R-PCA for both sunglass and scarf tests. This is because it also uses local approach. However, since the matching is done in probabilistic framework with the sum of the Mahalanobis distances between all the corresponding local parts, the effect of the occluded parts are not removed completely and still affects final matching.

## 5 Conclusion

In this paper we have dealt with the occlusion problem, which has been researched relatively less than illumination and pose problems in face recognition. We have proposed a new robust face recognition algorithm called S-LNMF to the partial occlusion, based on selective LNMF bases matching. Local occluded area in faces are first detected by a supervised 1-NN threshold classifier in PCA space, and then matching is performed in the LNMF subspaces with the selected occlusion-free bases. Experimental results demonstrated that the proposed algorithm could reliably recognize partially occluded faces with higher recognition rate than the existing methods.

## Acknowledement

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