Comparative Analysis of Partial Occlusion Using Face Recognition Techniques

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Abstract

This paper presents a comparison of partial occlusion using face recognition techniques that gives in which technique produce better result for total success rate. The partial occlusion of face recognition is especially useful for people where part of their face is scarred and defect thus need to be covered. Hence, either top part/eye region or bottom part of face will be recognized respectively. The partial face information are tested with Principle Component Analysis (PCA), Non-negative matrix factorization (NMF), Local NMF (LNMF) and Spatially Confined NMF (SFNMF). The comparative results show that the recognition rate of 95.17% with $r = 80$ by using SFNMF for bottom face region. On the other hand, eye region achieves 95.12% with $r = 10$ by using LNMF.

Keywords: Partial Face Occlusion, Non-Negative Matrix Factorization (NMF), Local NMF, Spatially Confined NMF.

1. INTRODUCTION

Face recognition deals with verifying or identifying a face from its image. It has received substantial attention and its performance has advanced significantly over the last three decades due to its value both in understanding how the face recognition process works in humans as well as in addressing many applications, including access control and video surveillance. For example, individuals who wear sunglasses, masks and veils are restricted to provide their full face due to occupation, contagious disease, privacy and religion practices [1]. Therefore, an automated partial face recognition system based on users' preference could be one of the potential solutions to solve the conflict arouse in [2, 3, 4] previously. For the past few years, researchers [5, 6, 7, 8] had studied on the possibility of using partial face as an alternative for recognition. [6, 7] had applied Radial Basis Function network in symmetric, that examined equal ratio of left side faces and right side faces. Their works had received encouraging results that even achieved the equivalent results of full face. However, the partition of face into left and right side is not practical for direct access control. Meanwhile, [9] had introduced masks on users, where different part of faces are covered and the partial face is evaluated using Lophoscopic Principle Component Analysis. Their algorithm was blemished because it is more computational expensive than Principle Component Analysis (PCA). In this paper, a partial face recognition system framework is compared in well-controlled environments when the full information of face is absent. We examined two scenarios. They are individuals who wear sunglasses and individuals who wear masks or veils during authentication. This means only bottom part of the face and top part of the face especially eye region will be taken into account during recognition.

On the other hand, the term 'controlled environment' refers to normal face recognition environment that capture full or partial 2D front face with limited users' support without intrude users' privacy.Linear subspace projection has been used extensively for feature extraction in face images. They include PCA [10], Linear Discriminant Analysis (LDA) [11] and neural network approaches [12]. These methods map the high dimensionality images into a lower-dimensional manifold and treat the images as a whole. [15] Proposed Non-Negative Matrix Factorization (NMF) for learning of face features. We made used of NMF and its variants ie. Local NMF [16] and Spatially Confined NMF (SFNMF) [17] to reduce the dimensionality of the raw image and at the same time to preserve as many salient features as possible. In addition, we compare our results with PCA as our baseline. The outline of the paper is organized as follow: Section 2presents the overview of feature extraction literature. Section 3 is denotes the experimental results and conclusion is discussed in Section 4.

2. FEATURE EXTRACTION LITERATURE

2.1 Principal Component Analysis (PCA)

Turk and Pentland [10] used Principal Component Analysis or known as Eigen Face to represent, detect and recognize faces. Images of faces, being similar in overall configuration, will not be randomly distributed in this huge image space and thus can be described by a relatively low dimensional subspace. The main idea of PCA is to find the vectors that best account for the distribution of face images within the entire image space. These vectors define the subspace of face images, which we call "face space". Each vector is of length N2, describes an N x N image, and is a linear combination of the original face images. Because these vectors are the eigenvectors of the covariance matrix corresponding to the original face images, and because they are face-like in appearance, they are named as "Eigen Faces".

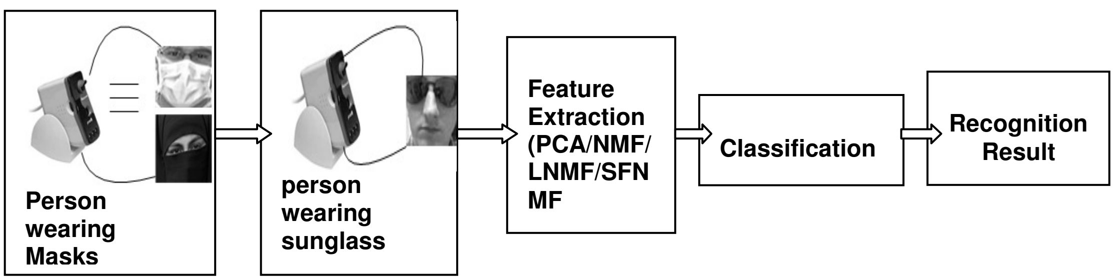


FIGURE 1: Comparison Framework.

FIGURE 2: Examples of AR database.

2.2 Non-Negative Matrix Factorization (NMF)

NMF finds an approximate factorization, where X is the raw face data into non-negative factors W and H. The nonnegative constraints make the representation purely additive (allowing no subtractions), in contrast to many other linear representations such as PCA. This ensures that the components are combined to form a whole in the non subtractive way. Given an initial database expressed by a n x m matrix X, where each column is an n-dimensional non-negative vector of the original database (m vectors), it is possible to find two new matrices (W and H) in order to approximate the original matrix:

$$X \approx \tilde{X} \equiv WH, \text{where } W \in \Re^{nxr}, H \in \Re^{rxm} \qquad (1)$$

We can rewrite the factorization in terms of the columns of *X* and *H* as:

$$x_j \approx \tilde{x}_j = Wh_j, \text{where } x_j \in \Re^m, h_j \in \Re^r \text{ for } j = 1, \ldots, n \quad (2)$$

The dimensions of the factorized matrices *W* and *H* are *n* x *r* and *r* x *m*, respectively. Assuming consistent precision, a reduction of storage is obtained whenever *r*, the number of basis vectors, satisfies $(n + m)\, r < nm$. Each column of matrix *W* contains basis vectors while each column of *H* contains the weights needed to approximate the corresponding column in *X* using the basis from *W*. In order to estimate the factorization matrices, an objective function has to be defined. We have used the column of *X* and its approximation of *X*=*WH* subject to this objective function

$$\Theta_{NMF}(W, H) = \sum_{j=1}^{n} \left\| x_j - Wh_j \right\|^2 = \left\| X - WH \right\|^2 \qquad (3)$$

This objective function can be related to the likelihood of generating the images in *X* from the basis *W* and encoding *H*. An iterative approach to reach a local minimum of this objective function is given by the following rules [18]:

$$W_{ia} \leftarrow W_{ia} \sum_{\mu} \frac{X_{i\mu}}{(WH)_{i\mu}} H_{a\mu} \qquad (4)$$

$$W_{ia} \leftarrow \frac{W_{ia}}{\sum_{j} W_{ja}} \qquad (5)$$

$$H_{a\mu} \leftarrow H_{a\mu} \sum_{i} W_{ia} \frac{X_{i\mu}}{(WH)_{i\mu}} \qquad (6)$$

Initialization is performed using positive random initial conditions for matrices *W* and *H*. Convergence of the process is also ensured.

C. Local NMF (LNMF)

LNMF [16] aims to improve the locality of the learned features by imposing additional constraints. It incorporates the following three additional constraints into the original NMF formulation.

(i) LNMF attempts to minimize the number of basis components required to represent X. This implies that a basis component should not be further decomposed into more components.

(ii) LNMF attempts to maximize the total “activity” on each component. The idea is to retain the basis with the most important information.

(iii) LNMF attempts to produce different basis as orthogonal as possible, in order to minimize the redundancy between different basis.

LNMF incorporates the above constraints into the original NMF formulation and defines the following constrained divergence as the objective function:

$$\Theta_{LNMF}(W,H) = \sum_{i}^{m}\sum_{j}^{n} X_{ij} \log \frac{X_{ij}}{[WH]_{ij}} - X_{ij} + [WH]_{ij} + \alpha C_{ij} - \beta \sum_{i} D_i \qquad (7)$$

where $\alpha, \beta, > 0$ are constants and $C = W^1W$ and $D = HH^T$ .The structure of the LNMF update for *W* is nearly identical to that in Equation 4, 5; differing only in the coefficient matrix *H*. The update for *H* now uses an element-by-element square root to satisfy the three additional constraints:

$$H_{a\mu} \leftarrow \sqrt{H_{a\mu} \sum_{i} W_{ia} \frac{X_{i\mu}}{(WH)_{i\mu}}} \qquad (8)$$

D. Spatially Confined NMF (SFNMF)

SFNMF method is implemented through a series of simple image processing operations to its corresponding NMF basis image. Firstly, a number of *r* original NMF basis are selected. Each basis is processed off-line to detect the spatially confined regions. The maximum values of the basis image are identified by adjust the threshold of a histogram of pixel values and followed by the morphological dilation operation to find a blob region. As a result, SFNMF basis images where only pixels in the detected regions have grey values copied from the corresponding pixels in the original NMF image are created. The remaining pixels are set to zero. SFNMF basis image only represents spatially confined regions. This is intuitive with the idea of recognition by components where spatially confined regions correspond to the important facial features regions such as eyes, eyebrows, nose and lips.

E. Face Recognition In Subspace

As in most algorithms that employ subspace projection, NMF, LNMF, and SFNMF basis are learned from a set of training images. Let □ denote the projection vector, the columns of *W* are NMF, LNMF or SFNMF basis images. During recognition, given an input face image, *Xtest*, it is projected to □ $=W^T X_{test}$ and classified by comparison with the vectors '*s* $□_T$ that were computed from a set of training images by using the L2 norm distance metric.

3. EXPERIMENTAL RESULTS

For experiment setup, a prototype was developed in MATLAB 7.0, and installed on a 1.60GHz Intel machine with 1Gb of RAM. The experiments are conducted by using Faces-94 Essex University Face Database [19], which consists of 153 subjects with 20 images per person. Face images are of size 180x200 in portrait format and after normalization, it becomes 30x61 for eye region images and 61x73 for bottom face region images. The first 53 subjects with 10 images are used for bases training with a total of 530 images. Another 100 subjects with 20 images are used for testing in the probe set with a total of 2000 images. In our experiments, False Reject Rate (FRR) and False Accept Rate (FAR) tests are performed. A unique measure, Total Success Rate (TSR) is obtained as FA + FR TSR= 1 - x100% Total number accesses

$$\text{TSR}=\left(1 - \frac{\text{FA + FR}}{\text{Total number accesses}}\right)\text{x}100\% \ . \ (9)$$

where FA = number of accepted imposter claims and FR =number of rejected genuine claims. For the FAR test, the first image of each subject in the testing set is matched against the first impression of all other faces and the same matching process was repeated for subsequent images, leading to 99,000 (4950 x 20) imposter attempts. For the FRR test, each image of each subject is matched against all other images of the same subject, leading to 19000 (190 attempts of each subject x 100) genuine attempts. An experiment is conducted by using a set of *r*, 2, 4, 6, 8, 10, 20, 40, 60, 80 and 100 to evaluate on the whole face, eye region and bottom face region. PCA with principal component of 100 is used as a baseline for comparison. Table 1 shows the results of face recognition for the user's whole face, compared with him/her wearing sunglasses, and subsequently a veil/mask. Thus, we are comparing whole face with eye region and bottom face region by adopting PCA, NMF and its variants ie. LNMF ,and SFNMF.PCA acts as a baseline in our study. By using this method, whole face recognition is able to achieve a high TSR of 96.17%. Eye region achieves TSR of 94.09% while bottom face region only 93.47%.Our previous study shows that NMF is slightly inferior than PCA [1, 17, 20, 21]. However, the variants of NMF are robust to performance and the processing time is greatly reduced. LNMF for whole face and eye region are able to achieve the highest TSR of 97.01% with *r* = 60 and 95.12% with *r* = 10 respectively. The bases learned are localized by imposing three additional constraints upon the original NMF basis [16]. On the other hand, bottom face region achieved the optimum TSR of 95.17% by using SFNMF with *r* = 80. The bases are processed through a series of image processing methods to abolish all noises in an image. Therefore, the basis learnt are said to be more spatially salient and local. Hence, SFNMF demonstrates improvements over NMF and LNMF [21].

Portion		Clean Face	Eye Region	Bottom Face Region
PCA	PC	100	100	100
	FAR	3.82	5.87	6.54
	FRR	3.87	6.13	6.49
	TSR	96.17	94.09	93.47
NMF	r	40	8	20
	FAR	5.57	6.73	7.84
	FRR	5.56	6.98	7-87
	TSR	94.43	93.23	92.16
LNMF	r	60	10	20
	FAR	2.99	4.81	5.50
	FRR	2.98	5.24	5.69
	TSR	97.01	95.12	94.47
SFNMF	r	40	20	80
	FAR	3.30	5.49	4.74
	FRR	3.29	5.69	5.33
	TSR	96.7	94.4	95.17

TABLE 1: Comparison of Partial Occlusion Face Recognition Results Using PCA, NMF, LNMF and SFNMF.

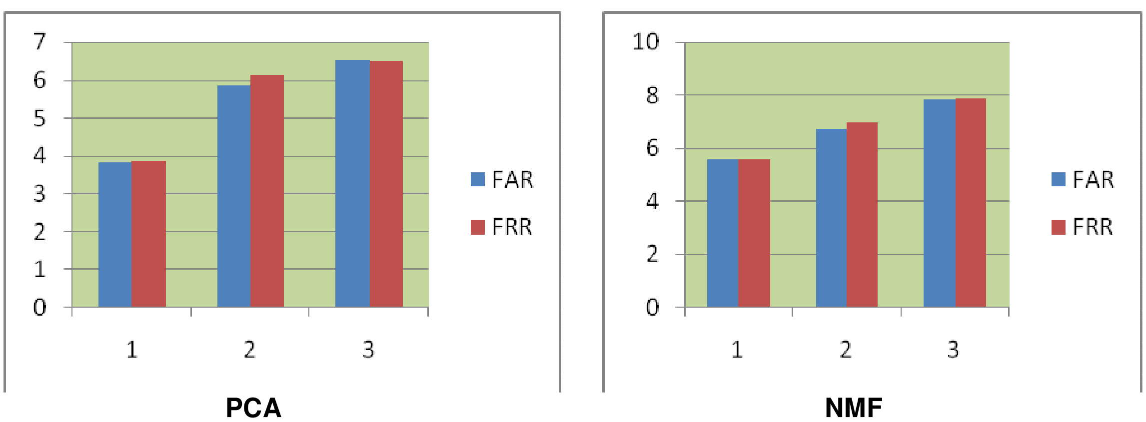
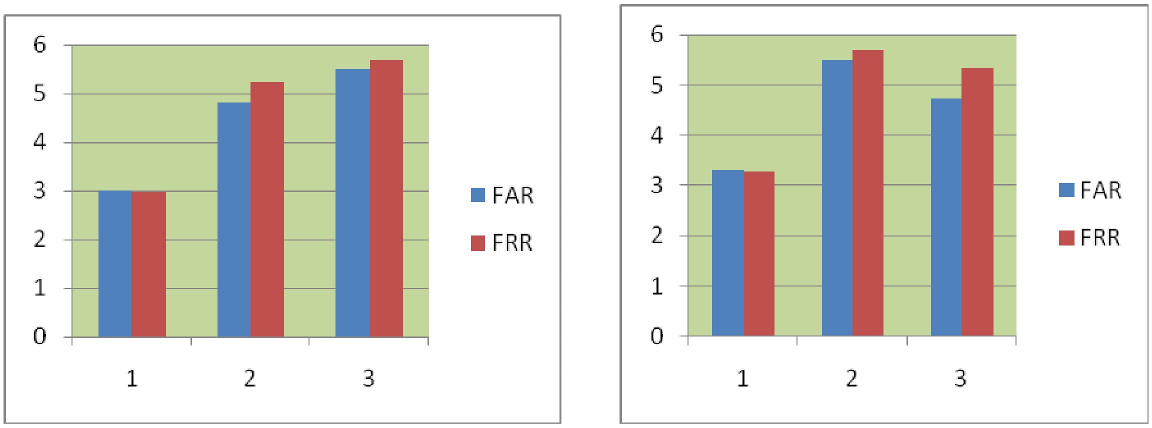


FIGURE 3: Graph Shows Comparison Results of PCA, NMF.



LNMF **SFNMF**

FIGURE 4: Graph Shows Comparison Results of LNMF,SF NMF.

Bottom Region	Total Success Rate
PCA	93.47
NMF	92.16
LNMF	94.47
SFNMF	95.17

TABLE 2: TSR Value of Bottom Region for PCA,NMF,LNMF and SFNMF.

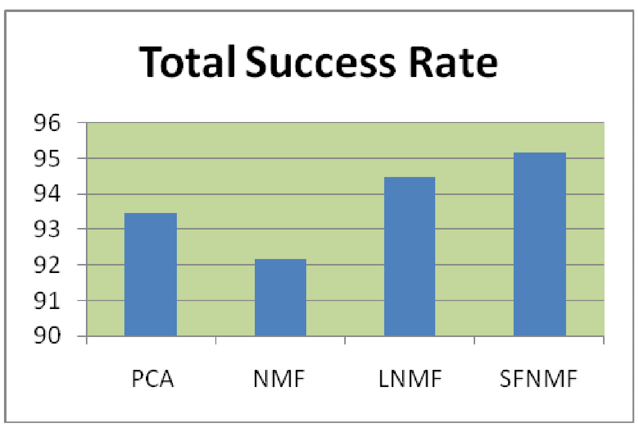


FIGURE 5: Graph Shows Total Success Rate of PCA, NMF,LNMF,SFNMF.

We observe that eye region and bottom face region are able to produce competitive outcomes whereby they only difference by 0.05%. However, the number of *r* in constructing eye region is only 10 while bottom face region acquires 80. This is due to the image resolution of eye region having smaller size with regard to bottom face region. On top of that, when the bases are locally salient, they require larger *r* to gain sufficient information to describe a particular face. The graph lies to the axis, the more powerful the recognition system is that SFNMF outperforms NMF and LNMF.

4. CONCLUSION

This paper shows a comparison results for only partial face information ie. Eye region and bottom face region for recognition. Partial face information is crucial in many situations to compensate the absence of full face images. For instance, airports and access control points where some people having facial defects use veils and others down with sickness covered their face with a mask, then our camera would capture only the eye region for authorization. On top of that, for some people wearing sunglasses, we will capture their bottom face region for recognition. Our findings show that bottom face region images itself are achieving a high recognition rate of 95.17% by using Spatially Confined NMF. The result is close to full face TSR of 96.7% of the same method. Therefore, partial face information possesses the unique features thus able to produce fairly good recognition rate. In the future, we would like to improve our feature extraction and classification methods so to increase and surpass the recognition rate of partial face corresponding to whole face.

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