Face Recognition Using Region-Based Nonnegative Matrix Factorization

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Abstract. This paper presents a new method of the face recognition using the nonnegative matrix factorization (NMF) and division of face into several regions. The proposed method divides facial images into 6 sub-regions, and then apply NMF to each sub-region producing basis images and encoding matrices. To recognize a target face, we compare the encoding coefficients of the target image with the encoding coefficients of training images. Test results show that our method is more robust to changes of illumination and facial expression, and occlusions than other methods, and that recognition with 3 sub-regions gives the best result.

Keywords: non-negative matrix factorization, region-based face recognition, local feature.

1 Introduction

Over the past few years, face recognition has been one of the most challenging research areas in computer vision. It is also very useful in any field which requires verification of the personal identity. One of difficulties in face recognition is that the recognition rate is degraded when there are some changes in the normal face such as aging, pose, facial expression, occlusions, make-up and plastic surgery. Thus, for the face recognition system to be reliable, we need a robust algorithm to such changes.

The facial feature representation for face recognition is divided into two approaches: the holistic approach and the feature-based approach. There are several well-known holistic representation techniques such as the principal component analysis (PCA) and the linear discriminant analysis (LDA) [2, 3]. Since this approach extracts global face features, it handles whole pixel information of face images.

The feature based approach, such as the elastic bunch graph matching (EBGM) and the active appearance model (AAM), analyzes explicit local facial features and their texture information with the geometric relationships [5–7]. EBGM describes faces using the Gabor features from the Gabor coefficients of face images. Since the dimension of the feature vector in this approach is too high, the dimensionality reduction method such as PCA or LDA is applied to the Gabor feature vector [8]. However, both approaches are sensitive to even small

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changes of background, illumination, occlusion, or pose variations [9]. Moreover, features are sensitive to the geometric transformation like rotation, translation, and scaling, which are caused by misalignment of facial components [10]. To deal with the problem of recognizing faces under natural occlusion, David Guillamet introduced the non-negative matrix factorization (NMF) technique in a face classification framework. After that, Lee and Seung proposed the part representation of data, like semantic features of text or parts of faces, using NMF [11, 12].

In this paper, we try to resolve the problem of different illumination conditions, facial expression, and natural occlusions with local region feature descriptor using NMF technique. The reminder of this paper is organized as follows. In Section 2, we explain the NMF technique briefly, and in Section 3, we introduce how the local NMF feature can be applied to face recognition. After presenting our experimental results in Section 4, we conclude in Section 5.

2 Nonnegative Matrix Factorization

NMF is one of the matrix factorization techniques, and a useful tool to find part-based representation of non-negative data [12, 13]. For the face recognition problem, each m-dimensional column vector of $m \times n$ matrix V represent one image of training data. Then, NMF is expressed as $V_{mn} \approx (WH)_{mn} = \sum_{r=1}^{i} W_{mr}H_{rn}$, where W is a matrix containing the r number of vectors called basis images, and H is matrix of r-dimensional vector set called encoding. r called rank is decided within $(n + m) \cdot r < m \cdot n$. An encoding is the coefficient of each basis image. Thus, an original object image is represnted as a linear combination of the basis images with corresponding encoding coefficients. There is a very important constraint in NMF, which is non-negativeness of base images and encoding. Non-negativity constraint leads to a part-based representation because it allows only additive combination without any subtraction in the object data. This is most different from other matrix factorization algorithms like PCA or Vector Quantization (VQ). The part-based representation extracts localized and relevant features, and finds a simple description. Therefore, we can get simpler and more reliable features with less computation time.

NMF algorithm is started with random initial matrices W and H. The matrix multiplication (WH) is updated iteratively until it become closed to V through maximizaing the cost function, $F = \sum_{i=1}^{n}\sum_{\mu=1}^{m} V_{i\mu}\log(WH)_{i\mu} - (WH)_{i\mu}$. During each iteration, multiplicative update rule is applied to get the approximate W and H :

$$H_{a\mu} \leftarrow H_{a\mu}\frac{(W^TV)_{a\mu}}{(W^TWH)_{a\mu}}, \tag{1}$$

$$W_{ia} \leftarrow W_{ia}\frac{(VH^{T})_{ia}}{(WHH^T)_{ia}},\ W_{ia} \leftarrow W_{ia}\frac{W_{ia}}{\sum_j W_{ja}} \tag{2}$$

This update rule is fast and easy to implement. Encoding H is coefficient to visualize the dependencies between original image V and basis image W.

Fig. 1. Six regions of a face image

3 Face Recognition Using Local NMF Features

3.1 Local Faces

Face features from whole face are very weak for face changes like different illumination, facial expression, and occlusion. In these conditions, we need to extract more robust face feature. Tuzel et al. introduced the region covariance matrix (RCM) using inside region of an image [17]. It gave a great result in face detection and object tracking, but failed for face recognition. Later, the Gabor based region covariance matrix (GRCM) was proposed and demonstrated better performance for face recognition [4].

For local face, we present a face with six regions which are five local face regions and one whole face as illustrated in Fig. 1.

The first region is a global representation of the face and next four regions describe left, right, upper, and lower parts of the face. The last region represents the middle part of the face. By using these regions, we can consider every part of the face region, but we can deal with changing conditions more smoothly.

3.2 Region NMF Features

By the result of NMF algorithm, we get the basis image W and the encoding H from original image V as described in Fig. 2.

The NMF features are considered locally significant features and each local part has a different spatial locality like eye, nose and mouth. Each column of the basis image W represents these locality in different locations for every face. From the result, one face uses at least one W feature vector, and every face has the encoding H as the coefficient of each vector W. The idea of recognizing face is simple. To recognize an image v, we need to compute the encoding h for v with the basis image W obtained from training with NMF. Then, the input image

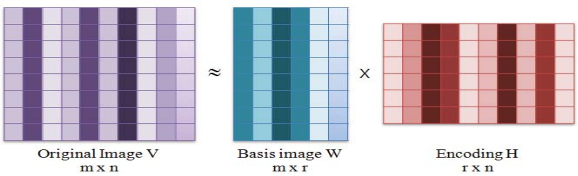

Fig. 2. Basic structure of NMF algorithm

v can be reconstructed by the basis image W and the estimated encoding h as following,

$$v_{mp} \approx (W_{m\times r})h_{r\times p} = \sum_{i=1}^{r}\sum_{a=1}^{m} W_{ai}h_{ip}, \tag{3}$$

Now, the encoding h for v is compared with each encoding of H from training face V. The key point of the proposed method is that we apply NMF to local faces, which produces namaly the region NMF feature. We extract the region NMF features from each region, calculate the Euclidean distance as the similarity measure between the training encoding H and the test encoding h, and then select the one with the highest similarity measure. To deal with the natural occlusion, illumination, facial expression and other noise, we select a subset of the six regions, which have better discriminative power than the full set of six regions. From our experiments and heuristics, three regions contain the important parts of the face, and may affect the recognition significantly. Therefore, the rest of regions, which are more unreliable parts of face, can be discarded. Finally, test face is recognized to the face k from the training faces (see Fig. 3).

$$d(H_j, h) = \min_j \left[\sum_{i=1}^{6} dist(H_i, h_i) - dist(H_j, h_j)\right] \tag{4}$$

$$= \sum_{i=1}^{6} dist(H_i, h_i) - \max_j \left[dist(H_j, h_j)\right] \tag{5}$$

The main advantages of the region NMF features are as follow:

- It is considered more about natural conditions such as illuminations, occlusions, facial expression, and noise etc.
- It does not need preprocessing of face images. Normally, all the images for training and test are cropped based on the centers of eyes because of normalizing pixel positions in a face.
- Although it reduce the dimensionality of face features, it shows good performance compared to other algorithms such as PCA, Gabor feature etc. We only need to consider encoding H of each region for recognizing the faces. It reduces computation time substantially.

The procedure of region based NMF approach for face recognition is illustrated in Figure 4.

Descending sort($dist(H_j^{(k)}, h_j)$) , $j = 1, \ldots, 6$

$$D(V_k, v) = \arg\min_k \left[\sum_{i=1}^{6} dist(H_i^{(k)}, h_i) - \sum_{j=1}^{3} dist(H_j^{(k)}, h_j)\right]$$

Fig. 3. The similarity calculation between training encoding k and test encoding based on Equation (5)

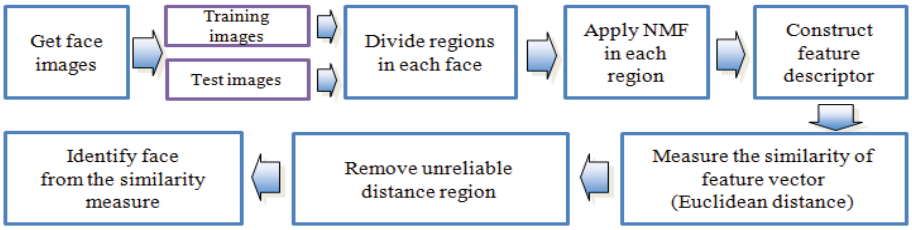

Fig. 4. The procedure of proposed algorithm

4 Experimental Results

4.1 Face Database

Our experiment was performed on AR database [1]. It contains two diferrent kinds of normal faces, facial expressions, illuminations, and four kinds of occlusions. Fig. 5 shows an example of one individual taken under these different conditions. From the database, 200 images were selected - that is twenty people with ten various images (10 males and 10 females). The Original image is 768×576 pixels but resized to 60×70 for efficiency. This process does not affect the accuracy of recognition at all. Among the 10 images per person, two normal face images (ARDB 01 shown in Fig. 5) were used for training and the remained eight for testing (ARDB 02-04 shown in Fig. 5).

The distinct characteristic of the proposed algorithm is that it produced good results without any preprocessing. In general, some preprocessing is needed for face recognition such as center of eye position normalization, background removal and pixel normalization with zero mean and unit variance.

4.2 Evaluation of the Algorithm

Fig. 6 shows recognition results with different ranks (r) when NMF is applied to each region of faces. From previous research, occlusion situations are the most

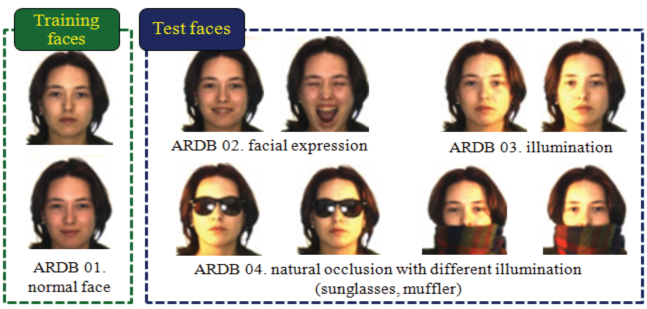

Fig. 5. An example of one individual in database

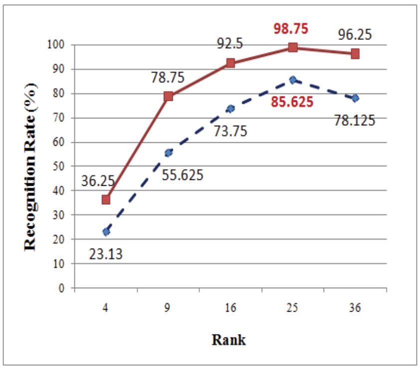

Fig. 6. (a)Recognition results according to various ranks: top red line is from non- occluded faces (ARDB 02-03 in Fig. 5); bottom blue line is from occluded faces (ARDB 02-04 in Fig. 5)

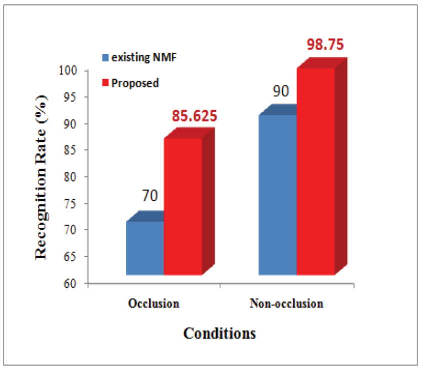

Fig. 7. Recognition accuracy comparison between existing NMF and Proposed NMF

obvious problems in face recognition. Therefore, our test performance is divided into two parts: non-occluded conditions with other various situations (ARDB 02-03 in Fig. 5), occluded conditions include non-occluded conditions (ARDB 02-04 in Fig. 5). The top red line is the recognition rate from non-occluded faces and the bottom blue line is from occluded faces. This figure represents that there are the much better result in non-occluded condition and rank 25 gives the best result using region NMF feature.

As can be seen in Fig. 7, we compared the recognition performances between existing NMF and the proposed method under non-occlusion faces and occlusion faces. By using a whole face in existing NMF, the recognition result is much lower than our approach.

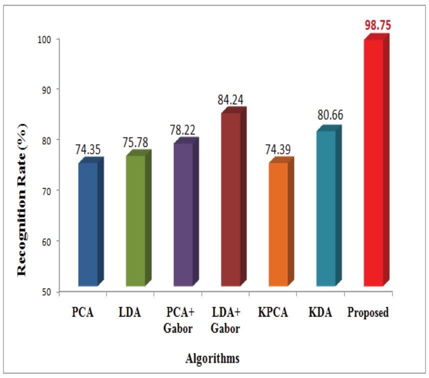

Fig. 8. Recognition accuracy comparison with non-occluded conditions

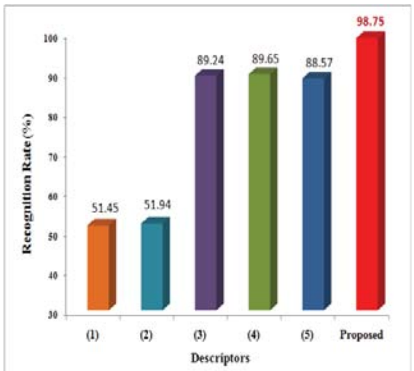

Fig. 9. Recognition accuracy comparison with region based methods

Table 1. Region based feature descriptor

Method	Descriptor
(1)	[x, y, I(x, y), $\lvert I_x \rvert$, $\lvert I_y \rvert$, $\lvert I_{xx} \rvert$, $\lvert I_{yy} \rvert$]
(2)	[x, y, I(x, y), $\lvert I_x \rvert$, $\lvert I_y \rvert$, $\lvert I_{xx} \rvert$, $\lvert I_{yy} \rvert$, (x, y)]
(3)	[x, y, g_{00}(x, y), g_{01}(x, y), …, g_{uv}(x, y)]
(4)	[x, y, I(x, y), g_{00}(x, y), g_{01}(x, y), …, g_{uv} (x, y)]
(5)	[g_{00}(x, y), g_{01}(x, y), … , g_{uv} (x, y)]
Proposed	[h_0, h_1, … h_r]

From Figure 8, we compare it with the various existing algorithms which are PCA (Eigenface), LDA (Fisherface), PCA+Gabor, LDA+Gabor, KPCA (Kernel Principal Component Analysis, and KDA (Kernel Discriminant Analysis) [2, 3, 14–16]. This experiment is under non-occluded conditions. The proposed algorithm is much more robust to various conditions with less dimension and computation time. Also, we got the highest performance.

Finally, region based methods are considered in Fig. 9. The detailed methods are listed in Table 1. In Table 1, x and y are pixel location and (x, y) is the edge orientation. $|Ix|$ and $|Ixx|$ are the first- and second-order derivatives, respectively. From (3) to (5), Yanwei Pang constructed new descriptor which is based on Gabor features in the regions. u and v define the orientation and scale of the Gabor kernels. The Gabor kernels are constructed by taking eight orientations ($u \in$ (0,..,7)) and five different scales ($v \in$ (0,..,4)). Lastly, r is defined as rank above, and we took 25 rank for best performance according to Fig. 6. As can be seen in Fig. 8-9, our proposed method experimentally shows that the region based NMF feature is a good feature for discriminating between different faces.

5 Conclusion

We have presented region based NMF technique to solve the problems of recognizing faces captured under the various conditions such as facial expression, occlusions and changes in different light conditions. NMF finds part-based compositions of data whereas it only allows the positive subspace. We applied this approach to the reliable sub-region face for high recognition rates under the partial changes of faces. Experimental results show that the region NMF feature is much more robust to recognize faces than using whole faces with other approaches. Also, it is simpler than other methods like Gabor based method or combination methods.

To apply our method in real world, face feature should be considered under the changes in time sequence and face scale changes etc. In addition, we expect to overcome the problem in occlusions for the better performance of face recognition in the near future.

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