A DISTANCE-ACCURACY HYBRID WEIGHTED VOTING SCHEME FOR PARTIAL FACE RECOGNITION

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Abstract

Face recognition has become a very popular research topic in the last 20 years. Most of the studies in the past focus on identifying a person using his/her holistic face images. But in real-life scenario, very often we need to identify a person given only partial face images. In this paper, we propose a distance-accuracy hybrid weighted voting scheme that gives weighting to the recognition results from partial face regions, and combines scores to generate the final recognition decision. With this method, we are able to perform face recognition even when only partial face images are available. We perform large-scale face recognition using CMU PIE database. Experimental results show that the proposed method is very successful, and the final recognition rate based on partial face images can be enhanced to be higher than the recognition rate based on holistic face images.

Keywords: Partial Face Recognition, Principal Component Analysis, Nearest Neighbor, Biometrics

1. Introduction

Face recognition has become an important topic in the field of biometrics, machine learning, pattern recognition and image processing. Most studies in face recognition focused on how to identify a person when we have his/her holistic face images. However, in practical situation, usually we can only acquire important parts of a face image. For example, video cameras inside ATM machines record video of every user. However, if an outlaw would like to use ATM for an evil purpose, he might wear a mask to cover lower half of his face. In such case, only upper half of his images is visible and can be used for face recognition. Another real-life example is that it is very often for people to wear sun-glasses in outdoor settings. Sun-glasses occlude the most discriminative regions on a face (the eye regions). Therefore, biometric recognition based on such images will have very low accuracy.

In this paper, we would like to investigate the face recognition problem when only parts of the face images are available. After understanding the recognition performance of each local face region, we further intelligently fuse the recognition scores of different regions and compute one final score based on the local recognition rates. According to our experimental results, final decision bases on such score will be robust toward illumination variation between training and test image sets.

The rest of the paper is organized as follows. We presented the literature review on section 2. In section 3 and 4, we presented details of our proposed method and the experimental results. Discussions and conclusions are presented at section 5.

2. BACKGROUND

Face recognition has attracted strong attention in the last two decades. In 1991, Turk et al. [1] proposed a holistic face recognition method based on principal component analysis (PCA), which is also known as “Eigenface”. In 2004, Yang et al. [3] extended the idea of PCA and proposed 2DPCA for face recognition, which does not transform images into column vectors, but directly uses training images to build “image covariance matrix”. Another important subspace learning method for face recognition is Fisher LDA [2], which is also known as “Fisherface”. In 2005, Li and Yuan [4] extended the idea of Fisherface and proposed 2DLDA, which directly extracts the proper features from image matrices based on Fisher’s LDA.

Face recognition has been recognized as a problem related to classification of high-dimension low-sample size (HDLSS) data, because in most cases, the number of training face images is much less than the dimension of the image. In 2007, Marron et al. [5] considered the disadvantage of the traditional SVM method on HDLSS problem, and proposed a Distance-Weighted Discrimination (DWD) method, which replaced the margin-based criterion of SVM by a different function of the distance from the data to the separating hyperplane. In 2010, Qiao et al. [6] improved DWD methods by developing optimal weighting schemes for various non-standard classification problems.

3. PROPOSED METHOD

In this study, we would like to investigate the recognition rate with respect to the individual parts on a face image. Such data reveals the discriminative power of individual face parts. After we acquire such data, we would be able to design an algorithm which takes advantage of the observed result and intelligently fuse the recognition results from individual face parts to compute a final score.

3.1 Partial Face Definition

We would like to divide a holistic face image into several parts. The principle of face division is that the partition of the face should be similar to the partially visible region observed from general video recordings from street surveillance so that our research results would be practical enough to be used in practical situations. According to such observations, we divide the holistic face into six regions: (1) Left Eye (2) Right Eye (3) Nose (4) Mouth (5) Upper Face (6) Lower Face, as shown in Fig. 1. We call each of the part as Partial Face Region (PFR).

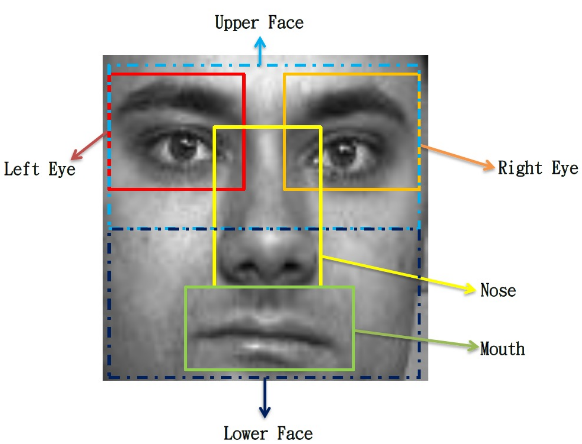

Figure 1. The definition of the partial face regions used in this study.

3.2 Recognition Performance based on PFR

After partitioning every face images in database into the six pre-defined region, we measure the recognition rate of each PFR. The recognition scheme used is the combination of PCA and One Nearest Neighbor (1NN) method. For each PFR, we compute the eigenvector set from training image set, and reduce the dimensionality of the partial face image by projecting them into the subspace spanned by the eigenvector set. During test stage, we project test image into the same subspace, and perform classification based on 1NN method. Thus, we get the recognition performance score for each PFR.

3.3 Voting Scheme for Final Decision

Now that we know the recognition performance score for each parts, next step is to design an intelligent method to combine the score from each parts into a single score. There are several weighting schemes that we can try.

- Uniform weighting: the most intuitive one is give the same weighting to each PFR.
- Distance weighting: A distance-weighted voting scheme is to adaptively give weighting to the recognition score for each PFR. The weighting for each PFR is inversely proportional to the Euclidean distance in PCA subspace between the test image and its nearest neighbor in the training set. Such scheme gives lower weighting to the hypothesis when the test partial face is far away from its nearest neighbor, and higher weighting when it is close to its nearest neighbor. The final classification decision is made by voting from each part.
- Accuracy weighting: if a PFR demonstrates higher recognition rate than all other PFR, we should give it higher weighting to vote. In this scheme, we let the weighting of PFR_i be proportional to the its baseline recognition rate r_i.
- Accuracy-Distance hybrid weighting: we can combine the idea of distance-weighting and accuracy-weighting into one scheme. It can be called Accuracy-Distance hybrid weighting. We let the weighting of the image I_j in PFR_i be proportional to r_i/d_j, where r_i is the baseline recognition rate of PFR_i, and d_j is the Euclidean distance between image I_j and its nearest neighbor in PCA subspace.

The overall description of the proposed algorithm is listed in Table 1.

Table 1. The description of distance-weighted voting scheme for partial face recognition in PCA subspace

Database Preparation:

Divide all images into six partial face region, denoted as PFR_i, i=1~6

For each training image

For each PFR, perform Principal Component Analysis (PCA) and project training images into PCA subspace

For each test image

1. *For each PFR, perform recognition using PCA+1NN, and return hypothesis h_i, i=1~6. At the same time, keep track of the Euclidean distance between the test partial face and its closest neighbor in training partial face.*
2. *The final classification decision for the holistic face is computed by weighted voting. The weighting scheme includes:*
   - i. *Uniform weighting*
   - ii. *Distance weighting*
   - iii. *Accuracy weighting*
   - iv. *Accuracy-Distance hybrid weighting*

4. EXPERIMENTAL RESULT

4.1 Database

We performed partial face recognition on subset of CMU PIE database [7], specifically, NoLight subset. This is because we would like to experiment with images with strong environmental illumination variation.

We partitioned every image in PIE-Nolight database into the six predefined PFR. The appropriate coordinate set of each PFR for PIE database is defined as the following:

Left eye <- face(5:40,5:40)

Right eye <- face(5:40,55:95)

Nose <- face(25:70,33:67)

Mouth <- face(65:100,25:75)

Upper face <- face (1:50,1:100)

Lower face <- face(51:100,1:100)

Where face(r1:r2,c1:c2) means to crop out a rectangle from the original face image at row r1 to r2, and column c1 to c2. Fig.1 shows an example of the partial face region.

Table 2. Index of the train set image used in our experiment

Training set	Image index	Description of the illumination variation pattern
1	1, 2, 17	Illumination from right side
2	15, 16, 21	Illumination from left side
3	7, 10, 19	All frontal illumination
4	1, 7, 16	Left, frontal and right illuminations

Table 3. Recognition rate for each PFR, and holistic face, in PCA subspace.

Regions \ Training set	1	2	3	4
Left eye	13.6%	35.6%	26.2%	45.1%
Right eye	35.0%	19.5%	33.8%	51.4%
Nose	15.6%	20.2%	10.8%	35.6%
Mouth	20.8%	18.6%	20.9%	56.8%
Upper face	21.1%	23.6%	22.7%	51.5%
Lower face	18.6%	20.6%	17.7%	48.2%
Holistic face	21.8%	23.2%	23.5%	56.8%

4.2 Baseline Experiments

In PIE-Nolight database, there are 65 subjects. Each subject has 21 images of illumination variation. In order to test the robustness of the proposed algorithm toward illumination variation between training and test images, we choose four different set of image index for training set. Consideration behind such choices is that we would like to make different training set have different illumination variation patterns.

Table 2 shows the image index for each of the four training set, as well as their corresponding illumination variation pattern. Fig. 2 shows example images for these four training set.

We performed classification on each of the six PFR and measure the recognition rate. Classification was also performed based on holistic face image, which will serve as a baseline for comparison purpose. Table 3 shows the recognition rate for all of the baseline experiments.

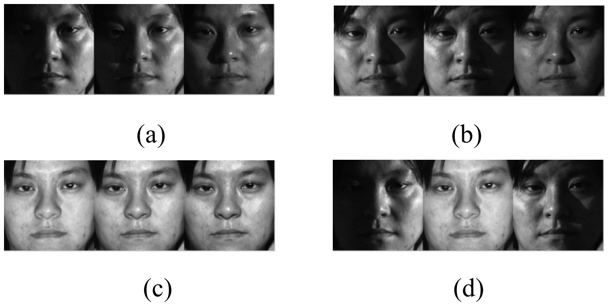

Figure 2. Example images of the training set. Sub-figure (a) –(d) corresponding to training set 1-4, respectively..

4.3 Classification Results of the proposed Algorithm

As described in section 3.2 and Table 1, we adaptively fuse the recognition result using the four proposed weighting scheme. The final classification hypothesis is decided by weighted voting. Fig. 3 shows the recognition rate for all of the four weighting scheme, using PCA as our projection subspace. We also experimented with FLDA subspace, and the results are shown in Fig. 4.

5. DISCUSSION/CONCLUSION

Table 3 tells us the recognition accuracy according to different PFR. We can see that when only partial face region is available for recognition, the recognition accuracy varies according to which part is seen more clearly and reveals more details for discrimination.

Generally speaking, when the holistic face is properly illuminated (as the case of training set 3), the ocular region (including left eye and right eye) seems most discriminative, as shown in the third column of Table 3 (results for training set 3), where face recognition based on holistic face image gives lower recognition rate compared to that of left and right eye region. In the case that left side is not properly illuminated, the right eye region becomes more discriminated than left eye and the holistic face, as shown in the first column of Table 3 (results for training set 1), and vice versa.

From Fig. 3, we see how the proposed method indeed enhances the recognition performance. For all training set, after applying the proposed weighting scheme, the final recognition rate is higher than the baseline (with holistic face). The experimental results implies that even when holistic face image is not available (faces are partially occluded), as long as some important regions are visible, it is still possible to perform accurate face recognition, to a degree that the recognition rate can be as high as (or better than) that based on holistic face images.

From Fig. 4, we can see similar trends. However, since the recognition rate with FLDA algorithm is relatively higher than PCA, the improvement is not very prominent. Nevertheless, the proposed hybrid weighting scheme seems to still enhance accuracy to some extent.

The relation between the proposed work and the prior work is that we applied the most popular face recognition algorithm for holistic face recognition into the framework for partial face recognition. Inspired by the idea of distance-weighted discrimination (as stated in [5] and [6]), we proposed a distance-accuracy hybrid weighted voting scheme that adaptively fuses the recognition score from each individual partial region, and produces one final score, which gives comparable (if not better) results to holistic face recognition.

In summary, in this work, we found that by dividing holistic face image into meaningful partial regions, and performing recognition on those regions, it is possible to enhance the recognition rate, compared to directly performing recognition on holistic face images. However, how to intelligently combine the score from partial region is important. In the work, we proposed four different weighting schemes (based on distance and regional accuracy) which adaptively fuse the recognition score so that the final recognition rate can be improved to some extent. Future work includes more detailed research about automatically discovering the discriminative region on a face, and more detailed experiments on large-scale database.

Acknowledgements

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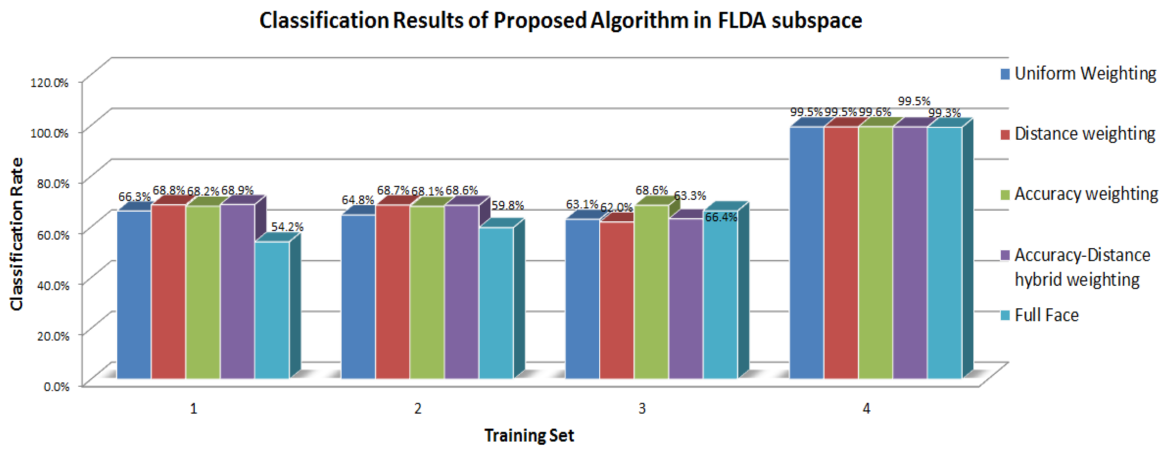

Figure 3. Face recognition rate based on four proposed partial face recognition scheme, as well as the holistic face (base-line), for all four training sets, in PCA subspace.

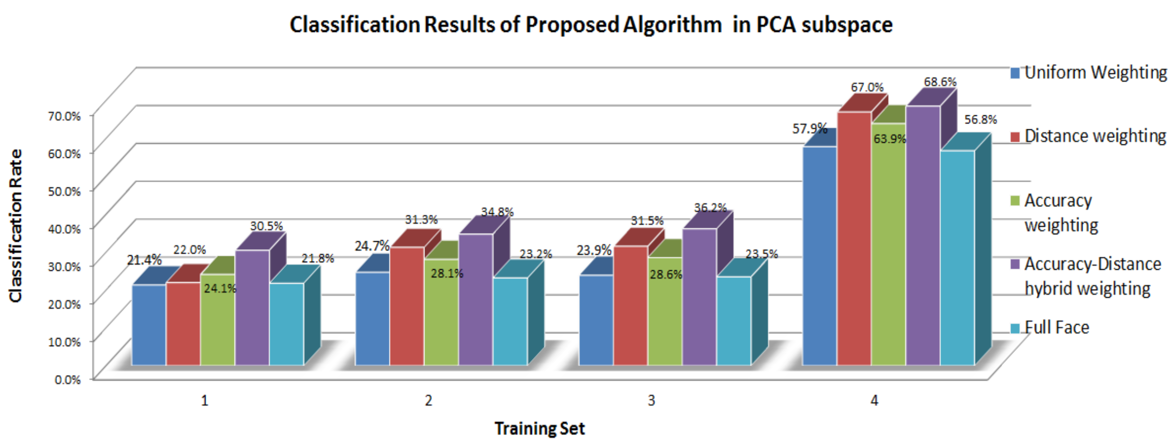

Figure 4. Face recognition rate based on four proposed partial face recognition scheme, as well as the holistic face (base-line), for all four training sets, in FLDA subspace

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