Information Fusion in Face Identification

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Abstract

Information Fusion of multi-modal Biometrics has attracted much attention in recent years. However, this paper focuses on the information fusion in single modals, that is, the face Biometric. Two different representation methods, gray level intensity and Gabor feature, are exploited for fusion. We study the fusion problem in face recognition at both the face representation level and the confidence level. At the representation level, both the PCA feature fusion and the LDA feature fusion are considered, while at the confidence level, the sum rule and the product rule are investigated. We show through experiments on FERET face database and our own face database that appropriate information fusion can improve the performance of face recognition and verification. This suggests that gray level intensity and Gabor feature compensate for each other, based on the feasible fusion.

1. Introduction

Over the past 20 years, numerous algorithms have been proposed for face recognition. Read detailed surveys [1][2][3]. In the following we will give a brief overview on face recognition methods.

In the early researches, methods based on geometric feature and template matching used to be popular technologies, which were compared in 1992 by Brunelli and Poggio. Their conclusion showed that template matching based algorithms outperformed the geometric feature based ones [4]. Therefore, since the 1990s, methods based on appearance have been in the dominant researches. In these methods, each pixel in a face image that is coordinated to a high-dimensional space and the classification is carried out in a low-dimensional feature space projected from the image space.

In some face recognition systems, the emerging applications based on automatic face identification require stringently on performance. For example, a high security access control system requires an extremely low false accept rate (<0.01%)[5]. Because of the nature of inexactitude in image acquisition and the feature extractor's vulnerability to light and pose variation in the face images, it is very difficult to reduce the false reject rate of a matcher when the specified false accept rate is extremely low. Many researchers have combined multiple biometrics(e.g., fingerprint and face [6][7][8] or face, fingerprint, and hand [9]), but this involves the additional cost of sensors and inconvenience to the users in providing multiple cues [5].

In the studies of various feature extraction algorithms, it has been reported in literatures that a same classifier often misclassifies different patterns. This suggests that different feature subsets offer complementary information about the classification task. A fusion scheme that harnesses various representations is likely to improve the overall system performance. The outputs of various feature extractors can be fused to obtain decisions that are more accurate than the decisions made by any one of the individual feature representations.

In this paper, we propose the method that combines the face image and its Gabor transformation in feature level and matching level respectively. Experimental results using the fused features on face databases of both FERET and our laboratory in identification and verification all outperform those of any individual feature representation.

2. Multi-modal face representation fusion

2.1 Face Representation

In our fusion method, we employ two face representations, that is, gray-level intensity and Gabor transform of the gray-level intensity.

The gray-level intensity was cropped and rectified according to the manually located eye positions. We scale the images to 64 pixels in height and 64 pixels in width. The histogram equalization of the gray-level intensity with mask is shown in Fig.1 (a).

The Gabor feature was obtained according to [10][11]:

$$\psi_{\mu,v}(z) = \frac{\left\|k_{\mu,v}\right\|^2}{\sigma^2} e^{-\frac{\left\|k\mu,v\right\|^2 \left\|z\right\|^2}{2\sigma^2}\left[e^{ik_{\mu,v}z} - e^{-\frac{\sigma^2}{2}}\right]}.$$

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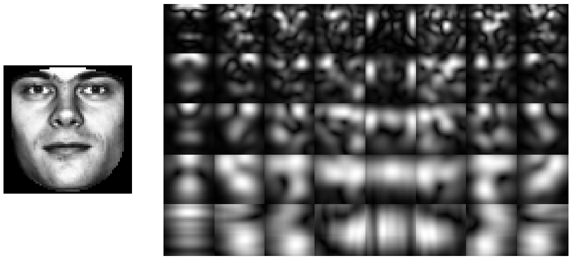
The visualization of the gray-level intensity's Gabor transform is shown in Fig.1 (b). We here choose five scales and eight orientations in Gabor transform.



(a) (b)

Fig.1. (a) Gray-level intensity
(b) Gabor transform of the gray-level intensity

In our methods, the gray-level intensity and its Gabor transform are the raw variables separately entering the feature extractor.

2.2 PCA and LDA

Nowadays, a technique commonly used for dimension reduction in computer vision- particularly in face recognition is principal components analysis (PCA)[12]. The feature vector of a gray-level intensity is the projection of the original face image on the dimension-reduced eigenspace.

Linear Discriminant Analysis (LDA) [13] is a class specific method in the sense that it represents data in a more useful form for classification. Given a set of N images $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\}$, assuming each image belongs to one of the c classes $\{X_1, X_2, \ldots, X_c\}$, LDA chooses a linear transformation matrix $\mathbf{W}$ when the ratio of the between-class scatter and the within-class scatter is maximized.

2.3 PCA Level Fusion

The features extracted by PCA from gray level intensity and the Gabor transform are combined firstly. Then the combined vector enters LDA. At last, the feature obtained by LDA is compared with the matching template before making the decision. The procedure of fusion in PCA feature level is shown in Fig. 2.

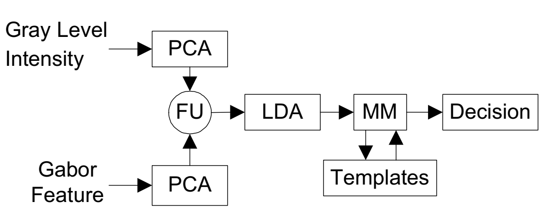


Fig.2. PCA Level Feature Fusion, FU: Fusion Module, MM: Matching Module

2.4 LDA Level Fusion

In contrast with the PCA level fusion, we get the LDA features from gray level intensity and the Gabor transform respectively and then combine these two features. The obtained feature vector is the input of the second LDA. The output of the cascade LDA is compared with the matching template before making the decision. The procedure of fusion in LDA feature level is shown in Fig.3.

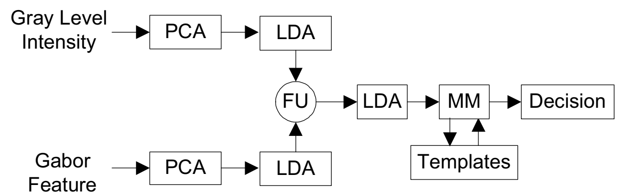


Fig.3. LDA Level feature fusion, FU: Fusion Module, MM: Matching Module

2.5 Confidence Level Fusion

In confidence level fusion, the LDA features from gray-level intensity and the Gabor transform are the input of matching module, then the combined result is compared with the matching modal before making the decision. The procedure of fusion in confidence level is shown in Fig. 4.

In confidence level fusion, we use the sum rule and the product rule [7].

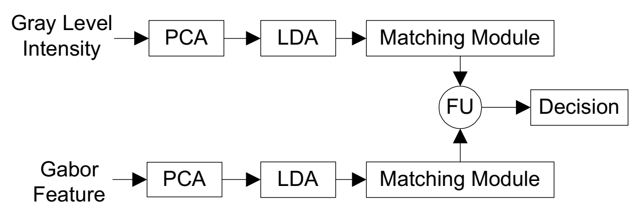


Fig.4. Confidence Level Fusion, FU: Fusion Module

3. Experimental Results

Identification and verification of a person's identity are two potential areas in application of face recognition systems. In identification applications, a system identifies an unknown face in an image. In verification applications, a system confirms the claimed identity of a face presented to it [14].

Thus, we have tested our face recognition algorithm in identification and verification respectively on the FERET test set which has been widely used to evaluate face recognition algorithms [15].

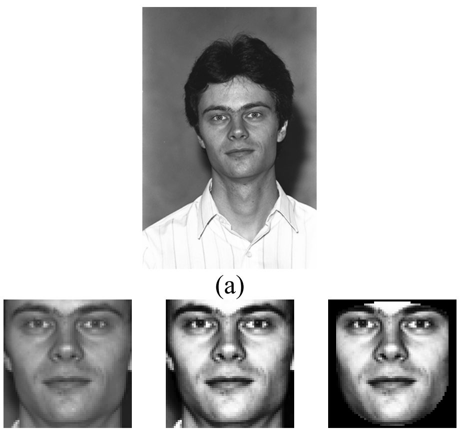
3.1 Experiments on FERET Face Database

There are 1002 images in the training set and all of the images come from parts of fa (regular facial expression) and fb (alternative facial expression) sets. The gallery consisted of images of 1,196 people with one image per person. In the probe category-FB, there are 1195 images.

All images are cropped and rectified according to the manually located eye positions supplied with the FERET data. We scale the images to 64 pixels in height and 64 pixels in width. Fig.5 (a) shows the original face image and Fig.5 (c) shows the cropped image (Fig.5 (b)) with histogram equalization. To reduce the affection of different hairstyles and backgrounds, a mask is put on the face image. The masked image is shown in Fig.5 (d).

The experimental results of verification and the identification are shown in table 1 and Fig.6 respectively. The former shows performances of the algorithms for identification, and the latter shows performances of the algorithms for verification.

In the verification problem, the equal error rate is the point at which the percentage of correct verifications equals one minus the percentage of false alarms [16].



(a)

(b) (c) (d)

Fig.5. (a)original image (b) cropped image (c)Histogram Equalization (d) put on mask

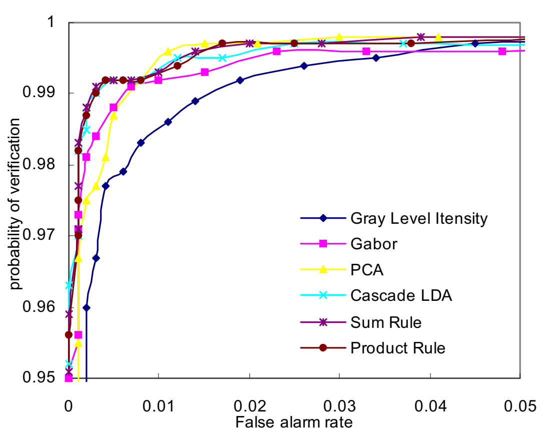


Fig.6. ROC curve for verification task on FERET FB

Table 1 the recognition rate of identification and the equal error rate of verification in FERET **FB** test set

Methods	Recognition Rate	Equal Error Rate
Image	0.961	1.25%
Gabor	0.972	0.8%
LDA Feature Fusion	0.977	0.8%
PCA Feature Fusion	0.974	0.8%
Sum rule	0.981	0.75%
Product rule	0.982	0.8%

3.2 Experiments on JDL Face Database

We also test the fusion method on our own face database, JDL face database. Face images were collected in our laboratory from 500 subjects. Both the training set and the test set are subsets of the 500 subjects. In the training set, there are 300 subjects and each subject has about 14 images. In the test set, there are 6577 images of the 500 subjects and all of the images are different from the training images. After the same preprocess as the images in FERET set described above, Fig.5 and Fig.7 shows the example faces in our own face database. The experimental results of verification and the identification are shown in table 2 and Fig.8 respectively.

Fig.7. Example faces in our laboratory's face database

Table 2 the recognition rate of identification and the equal error rate of verification in our own face database

Methods	Recognition Rate	Equal Error Rate
Image	0.712	8.8%
Gabor	0.849	4.8%
LDA Feature Fusion	0.885	4.1%
PCA Feature Fusion	0.885	3.95%
Sum rule	0.856	5.1%
Product rule	0.845	6.4%

4. Conclusion

Information Fusion of multi-modal Biometrics has attracted much attention in recent years. However, this paper focuses on the information fusion in single modals, that is, the face Biometric. We study the fusion problem in

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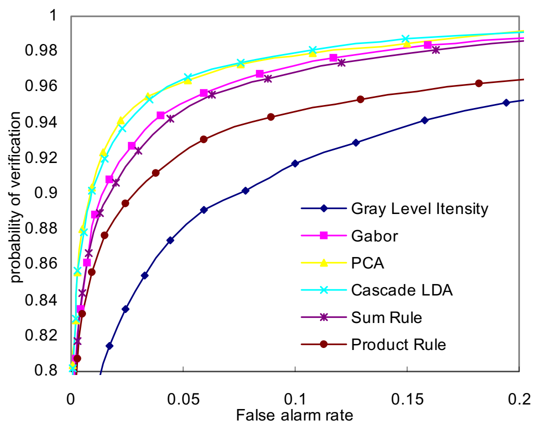

Fig.8. ROC curve for verification task on our own face Database

face recognition at both the face representation level and the confidence level. Two different representation methods, gray level intensity and Gabor feature, are exploited for fusion. At the representation level, both PCA feature fusion and LDA feature fusion are considered, and at the confidence level, sum rule and product rule are investigated. Our experiments on FERET face database and our own face database have shown that appropriate information fusion can improve the performance of both face recognition and verification. This suggests that gray level intensity and Gabor feature have provided different information of identity that can compensate for each other, based on the feasible fusion.

In addition, fusion methods at the representation level is more robust than those at the confidence level, which suggests that information fusion should be conducted as early as possible in the whole recognition procedure.

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