REAL-TIME FACE VERIFICATION USING MULTIPLE FEATURE COMBINATION AND A SUPPORT VECTOR MACHINE SUPERVISOR

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ABSTRACT

This paper proposes a novel face verification algorithm based on multiple feature combination and a support vector machine. The main issue in face verification is to deal with the variability in appearance. It seems difficult to solve this issue by using a single feature. Therefore, combination of mutually complementary features is necessary to cope with various changes in appearance. From this point of view, we describe the feature extraction approaches based on multiple principal component analysis and edge distribution. These features are projected on a new intra-person/extra-person similarity space that consists of several simple similarity measures, and are finally evaluated by a support vector machine supervisor. From the experiments on a realistic and large database, an equal error rate of 0.029 is achieved, which is a sufficiently practical level for many real-world applications.

1. INTRODUCTION

As the need for information security increases, biometrics technology based on personal bio-information has recently attracted considerable attention. Among these biometrics technologies, the face verification technology is considered as competitive since it is more convenient than other biometrics technologies. Numerous studies on face verification have been explored over the years [1][2], and there are several commercial systems, such as "FaceIt" [3], "FacePASS" [4], and "Zn-Face" [5]. In spite of these efforts, automatic face verification is still very difficult in computer vision. The main problem is caused by variability in appearance due to changes in lighting condition, pose, expression and aging.

We first propose a novel face verification algorithm based on multiple feature combination and a support vector machine. It is difficult to deal with face verification problems by using a single feature due to variability in appearance [6]. So we try to solve these problems by combining multiple features (eigenface, eigenUpper, eigenTzone, edge distribution).

There are several considerations for building a real-world face verification system. The system must manage memory efficiently and easily adapt to addition or removal of persons from the face database. We also discuss these important practical considerations.

Using the proposed algorithm, we build the face verification system for the security of PC in the office. For the realistic experiments, we use two separate databases consisting of images captured by a USB camera in general office environments.

This paper is organized as follows. In Section 2, the overview of our face verification system is described. The detailed description of the proposed features is given in Section 3. Section 4 deals with a novel similarity space and a support vector machine supervisor. An evaluation model and the experimental results are shown in Section 5. Finally, Section 6 concludes this paper.

2. FACE VERIFICATION SYSTEM OVERVIEW

The flow of our face verification system is shown in Figure 1. The first step in our system involves image preprocessing in order to establish correspondence between face images to be compared. Since our system is based on gray level template matching, this preprocessing step is essential. This step is divided into two processes, geometric normalization for adjusting the location of facial features and photometric normalization for improving the quality of the face image.

In geometric normalization, based on manually localized eye positions, we rotate, size scale, and then crop the face region from the original image.

In the photometric normalization, in order to remove the interference background, we put a mask on the cropped face image as shown in Figure 2(b). In order to compensate for illumination, we apply histogram equalization on the face image except the mask region. As part of intensity normalization, we apply standardization, that is we subtract the mean value of the face image from each intensity value and divide by standard deviation.

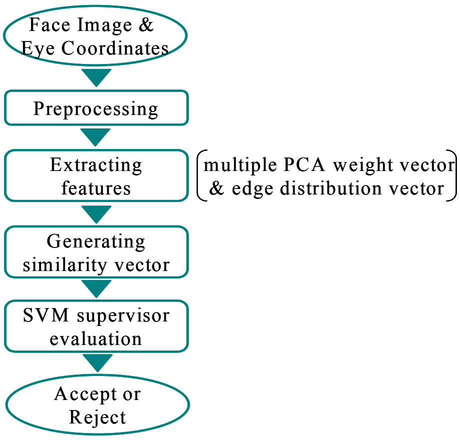

Figure 1. The flow chart of our face verification system

In the feature extraction step, we extract the multiple principal component analysis vectors based on three face regions and the edge distribution vector of the face image.

These features are projected on the new intra-person/extra-person similarity space that consists of several simple similarity measures, and are finally evaluated by the support vector machine supervisor.

3. FEATURE EXTRACTION

The selection of good features representing the face is the main factor to improve verification performance. In this section, we describe very simple and efficient features.

3.1. Multiple PCA

Principal component analysis(PCA) is the optimal linear method for reducing the dimensionality of a data set while retaining as much variation as possible in the data set. Based on this central idea of PCA, the eigenface method is the most widely used method for representation and recognition of human faces [7].

Among the face verification techniques based on the eigenface method, it is reported that the extension of the eigenface to facial features leads to an improvement in the recognition performance [8]. This can be viewed as a modular representation of a face, where a coarse description of the whole face is augmented by additional details in terms of salient facial features. Though these additional facial features improve performance, in order to select the correct regions of features, the computational expense increases and detection errors occur.

Therefore, this paper proposes eigenUpper and eigenTzone as shown in Figure 2. Since the proposed feature regions are selected just based on the eye positions, additional computational expense and a detection error are minimized.

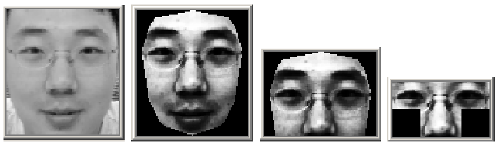

Figure 2. The selected face region for multiple PCA : (a)cropped face region, (b)eigenface, (c)eigenUpper, and (d)eigenTzone.

eigenUpper. This model is for compensating the changes in expression. We know that among salient facial features a mouth is most sensitive to expression instinctively. Therefore, just by removing a mouth region, we can compensate for the changes in expression such as smiling and talking.

eigenTzone. This model includes only the main facial features, eye and nose. eigenTzone is designed for compensating for illumination. So, the regions sensitive to illumination, such as forehead and cheek are excluded. Also, the T-zone of a face contains very important details for representing human faces.

3.2. Edge Distribution

We consider that edge information is another important factor for representing human faces. It is well known that a caricaturist represents the characteristics of a human being using only several lines. From the point of view, we have a consideration that the edge distribution on a human face becomes a good feature for face verification.

In our algorithms, the edge density of face region is normalized by the value of 25% edge density as shown in Figure 3. The procedure of edge density normalization is as follows.

1) Make the edge image using a Sobel edge operator.
2) Make the distribution histogram of edge intensity.
3) Determine the threshold(θ) at 25% rank from the highest intensity.
4) Select pixels which has a higher intensity than the threshold(θ).

Then, this normalized binary edge image is divided into 10×10 size block and each block has the edge density value itself as the feature value. In our system, the size of cropped face region is 80×90, so the edge density vector consists of 72 elements. Our algorithm is very simple, and we can overcome the weakness of edge operation to illumination efficiently.

4. SUPPORT VECTOR MACHINE SUPERVISOR

A Support Vector Machine(SVM) is basically a binary classifier based on the statistical learning model using the high dimensional virtual feature space [9].

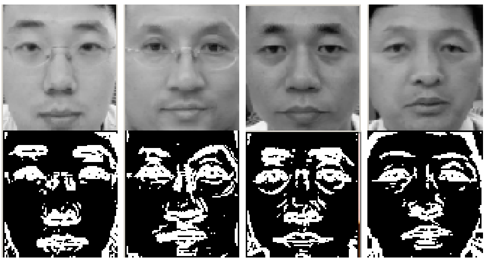

Figure 3. The cropped sample image (top row) and the corresponding binary edge image normalized by the value of 25% edge density (bottom row).

In our algorithm, we classify the multiple PCA features and the edge distribution feature using a support vector machine. At this time, if these feature vectors are fed to SVM, one SVM per enrolled person trained by each person's features is necessary. A large number of SVMs causes the additional expense, the processing speed decrease and the memory increase in enroll process.

As the solution to this problem, we define a novel intra-person/extra-person similarity space that represents the correlation between the two feature vectors.

The projection of the two feature vectors(one for the input face and the other for the enrolled face) on the similarity space is performed by several simple similarity measures.

They are :

1) Euclidian distance(ED)
2) L1-norm distance
3) Mahalanobis distance
4) Correlation
5) Covariance
6) ED between the first part of PCA vector
7) ED between the middle part of PCA vector
8) ED between the last part of PCA vector

By the above-mentioned similarity measures, the 8 similarities are created between the eigenface weight vector of the input face and that of the enrolled face. For eigenUpper and eigenTzone, the same process is adopted. Also one similarity value is created between two edge distribution vectors by Euclidian distance. By the combination of 3 similarity vectors(8 elements) and 1 similarity, finally similarity vector with 25 elements is created.

Since the similarity vector is created based on the similarity of two feature vectors, it is clustered into two classes in 25 dimensional similarity space. That is, the intra-person similarity vector class and the extra-person similarity vector class. Each class is clustered around similar position regardless of person's characteristic and the number of persons in the database. And then SVM, the binary classifier, classify these classes efficiently.

By defining a new similarity space, we can use just one SVM for classification, and alleviate the speed and memory problem.

5. EXPERIMENTAL RESULTS

For experiments, we use the Inha univ. database and the ETRI database. These databases are constructed in order to evaluate the face verification system for the security of PC in the office. Therefore, we capture images by a USB camera in general office environments and target the frontal face images without constraints on illumination and expression. The size of an image is 320×240 pixels and the type is 24bit RGB color. The Inha univ. database and the ETRI database consist of 2,100 samples from 105 oriental persons and 1,120 samples from 56 oriental persons, respectively.

In our evaluation model, the Inha univ. database is used just for making the three eigenfactors(eigenface, eigenUpper, eigenTzone). We test only on the ETRI database. Therefore, persons who participate in making the eigenfactors don't exist in the database for the tests and eventually eigenfactors are always fixed independent of the database. In a real-world system, the composition of the members in the database is always variable. If we don't have the fixed standard eigenfactors, we have to make the eigenfactors based on the current database. In this case, we have to remake them whenever persons are added to the current database. Actually, this frequent update of eigenfactors causes the useless computational expense and above all influences the feature vectors of the existing enrolled persons. For these reasons, by designing the above-mentioned evaluation model, we wish to do realistic and accurate experiments.

In the ETRI database composed of 20 images per person, by considering the size of enroll data, enroll time, user convenience, verification performance, we empirically decide to use 5 images for enrollment and the remaining 15 images for test.

The similarity vector (S) between the feature vector of the input image (If) and the 5 feature vectors of enrolled images (Ef) is created as follows :

$$S_k = \underset{i=1}{\overset{5}{MAX}}\left(M_k\left(If, Ef_i\right)\right) \tag{1}$$

where i is the index of the enrolled image, k is the index of the similarity vector element ($1 \le k \le 25$), and M is the similarity measure.

Table 1 shows the equal error rate(EER) for the several feature vectors and the similarity measures. As expected, the proposed algorithm outperforms eigenface weight feature vector by 0.05~0.06.

As a single similarity vector, the equal error rate of eigenUpper and eigenTzone is 0.046 and 0.064 respectively. The performance of these eigenfactors is almost equal to that of eigenface and by combining these eigenfactors, we can improve the system performance.

Table 1. Comparison of equal error rate for several feature vectors and similarity measures on the ETRI database

Feature Vectors	Similarity Measures	EER
Eigenface Weight Vector	Euclidian	0.093
	L1-norm	0.081
	Mahalanobis	0.083
	Correlation	0.086
	Covariance	0.086
Edge Distribution	Euclidian	0.098
Eigenface Similarity Vector	SVM Supervisor	0.055
EigenUpper Similarity Vector		0.046
EigenTzone Similarity Vector		0.064
Multiple PCA Combination		0.039
Edge Distribution & Multiple PCA Combination		0.029

Table 2. Equal error rate of our technique on the FERET database

Probe category	Gallery Size	Probe set Size	EER
FB	1196	1195	0.045
Duplicate I	1196	722	0.155
Fc	1196	194	0.096
Duplicate II	1196	234	0.201

These results prove that the selected regions of eigenUpper and eigenTzone are suitable and give the efficient details for representing human faces.

As a single feature vector, the equal error rate of edge distribution feature vector is 0.098, which is similar to that of the basic eigenface method. And in combination with the multiple PCA features, the performance is improved remarkably. This result means that the proposed edge distribution feature is good enough to represent faces and the combination of the different feature extraction approaches (PCA texture-based approach / edge-based approach) is a good solution to the real-world problems.

Note that we use the fixed standard eigenfactors on the above experiments. The result shown in Table 1 is very encouraging and is a sufficiently practical level for many real-world applications.

Table 2 shows the equal error rate of our technique on the FERET database [10]. The experiment follows the FERET verification testing protocol [11]. Considering that our eigenfactors are created by face images of orientals, the experiment on the FERET database composed of various races is somewhat challenging. Nevertheless, our algorithm shows comparable performance with those of other algorithms evaluated on the FERET test [12].

6. CONCLUSION

In this paper, we propose feature extraction approaches based on multiple principal component analysis and edge distribution. Also, we address several problems for building real-world system, by introducing a novel intra-person/extra-person similarity space and fixed standard eigenfactors. From the experiments on a realistic and large database, an equal error rate of 0.029 is achieved.

We are now researching a new feature extraction approach for compensating many real-world problems and testing performance continuously.

7. ACKNOWLEDGMENTS

Portions of the research in this paper use the FERET database of facial images collected under the FERET program [10][11].

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