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An Efficient Face Recognition using Feature Filter and Subspace Projection Method

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Purpose In this paper we proposed cascade feature filter and projection method for rapid human face recognition for the large-scale high-dimensional face database.

Materials and Methods The relevant features are selected from the large feature set using Fast Correlation-Based Filter method. After feature selection, project them into discriminant using Principal Component Analysis or Linear Discriminant Analysis. Their cascade method reduces the time-complexity without significant degradation of the performance.

Results In our experiments, the ORL database and the extended Yale face database b were used for evaluation. On the ORL database, the processing time was approximately 30-times faster than typical approach with recognition rate 94.22% and on the extended Yale face database b, the processing time was approximately 300-times faster than typical approach with recognition rate 98.74 %.

Conclusion The recognition rate and time-complexity of the proposed method is suitable for real-time face recognition system on the large-scale high-dimensional face database.

Key Words Face Recognition · Feature Filtering · Subspace Projection.

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Introduction

Over the past years, various face recognition technique have been developed and applied to authentication and surveillance. Among them, the most popular face recognition method is based on the principal component analysis (PCA) and linear discriminant analysis (LDA) method. PCA captures the subspace to maximize scatter of data and LDA captures the subspace to maximize between scatter of data and minimize within scatter of data.

Since PCA (1) and LDA (2, 3) method, however, project features onto the linear subspaces, their computational time depends on the dimension of features and the number of linear subspaces. Therefore, in the large-scale high-dimensional feature database, the PCA and LDA based system spend too much time on their projection and distance computation.

In this paper, we propose an efficient face recognition method using cascade feature filter and subspace projection. The main difference between feature filter and subspace projection are described on the Fig. 1. Since the feature filter approach selects only the relevant features, the computational time of distance measure between images can be reduced, but it loses the information of entire structure. On the other hand, the subspace projection approach maintains the information of entire struc-

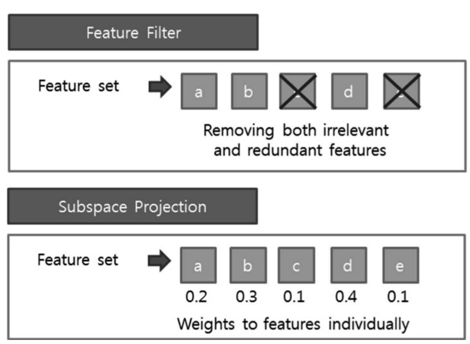

Fig. 1. The difference between feature filter and subspace projection.

ture and project features onto other linear spaces. As a result of their cascade structure, we have compromise performance and time-complexity. In our method, the Fast Correlation-Based Filter (FCBF) (4) is used for the feature filtering. The FCBF remove irrelevant and redundant features. After feature selection, the PCA or LDA is adopted to find discriminant subspaces.

Materials and Methods

Our method composed of two parts, which are feature filter and subspace projection.

In the feature filter step, the irrelevant features are removed from the entire feature set using symmetrical uncertainty (SU) between feature vectors and classes.

$$H(X) = \Sigma_i P(x_i) * \log_2 P(x_i) \quad (1)$$

$$H(X|Y) = H(X, Y) - H(Y) \quad (2)$$

$$IG(X, Y) = H(X|Y) + H(Y) \quad (3)$$

$$SU(X, Y) = 2 * IG(X, Y)/(H(X) + H(Y)) \quad (4)$$

The entropy, conditional entropy, information gain and symmetrical uncertainty are described in (1), (2), (3), and (4), respectively. The relevant features are features with the high SU between n-dimensional feature vector, $X = [x_1\ x_2 \cdots x_n]$, and the classes C. we describe the SU between i-th feature vector and class to $SU_{i,c}$ and the SU between i-th feature vector and j-th feature vector to $SU_{i,j}$. Firstly, relevant features are selected by $SU_{i,c} \geq \theta$, where θ is pre-defined threshold. After the selection of relevant features, the redundant features are filtered progressively by using the criterion of the redundant feature, $SU_{i,c} \leq SU_{i,j}$. Fig. 2 describes selected features from the ORL database and the extended Yale face database b.

In the subspace projection step, PCA or LDA adopted to find discriminant subspace on the training set, which is filtered with FCBF.

$$J_{PCA}(w) = w^T S_T w \quad (5)$$

$$J_{LDA}(w) = \frac{(w^T S_B w)}{(w^T S_W w)} \quad (6)$$

Equation (5) and (6) are PCA and LDA criteria, respectively, and S_T is total scatter matrix, S_B is between-class scatter matrix, S_W is within-class scatter matrix and w is optimal subspace for each criterion.

There are two combinations of our method and we call FCBF followed by PCA to FCBF_PCA and FCBF followed by LDA to FCBF_LDA.

Results

We evaluate the PCA, LDA, and FCBF_PCA, FCBF_LDA on the ORL dataset (5) and the extended Yale Face Database B (6) with 3.4 GHz CPU and 16.00GB RAM. In the ORL database, there are 40 subjects and 10 difference images for each subject

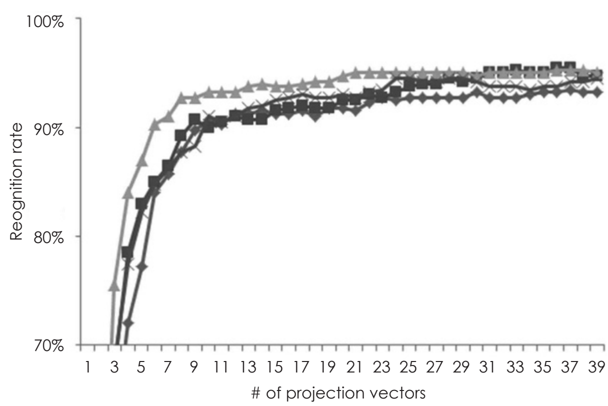

Fig. 3. Recognition rate according to the number of projection vectors on the ORL database.

Fig. 2. Selected discriminant features from the samples of (A) the ORL database and (B) the extended Yale face database b. (left is original image and right is its corresponeding selected features).

Table 1. Recognition rate (mean ± std %)

	PCA	LDA	FCBF_PCA	FCBF_LDA
ORL Database (39 basis)	93.75±1.13	94.95±1.09	94.22±1.12	93.57±1.14
Extended Yale face database b (37 basis)	77.81±0.85	99.50±0.12	93.49±0.61	98.74±0.19

Table 2. The number of features used in subspace projection

	PCA	LDA	FCBF_PCA	FCBF_LDA
ORL database	10304	10304	297~344	297−344
Extended Yale face database b	32256	32256	139~158	139−158

with small variance in pose, illumination and facial expression. The size of each image is 92×112 with gray-scale pixel. In the extended Yale face database b, there are total 16128 images of 28 subjects under 9 pose and 64 illumination condition. We used the cropped version which manually aligned, cropped and then resized to 168x192 images. And we also apply histogram equalization to reduce effects of illumination variance.

We evaluate databases with 2-fold cross validation and repeat it 10 times to reduce the variation of results. Fig. 3 shows the recognition rate with respect to the number of projection vectors.

Discussion

According to our experimental results as shown in Table 1 and Table 2, FCBF_PCA and FCBF_LDA are 30 times smaller than typical PCA and LDA based face recognition technique on ORL database and 300 times smaller on extended Yale face database b without significant degradation of the performance. As a result, we prove our proposed method proper for the large-scale high-dimensional feature database with compromise performance and time-complexity for real-time system.

Conclusion

In this paper, we propose an efficient face recognition system using feature filter and subspace projection method. Their experimental results show that the proposed method has a lower time-complexity than typical method while there is no significant performance degradation. Therefore, our proposed method is suitable for the real-time face recognition system on the large-scale high-dimensional feature database.

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