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Multi-Feature Combination Face Recognition Based on Kernel Canonical Correlation Analysis

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Abstract

In order to improve the recognition rate of face and use the complementary advantages between multi-feature and classifier, the paper proposes multi-feature combination face recognition method (KCCA - MF) based on kernel canonical correlation analysis. First extract LBP features and Gabor features of face images, then fuse these two kinds of features by using the analysis algorithm relating to kernel canonical correlation to eliminate redundant features. Finally, apply K neighbor algorithm and supporting vector machine (SVM) to establish the combination face classifier, and use three classic face libraries for simulation analysis. The results show that comparing with the other face recognition methods, KCCA - MF improves the accuracy and efficiency of face recognition, so it can satisfy the real-time requirement of face recognition.

Keywords*: face recognition, Gabor feature, LBP feature, kernel canonical correlation analysis*

1. Introduction

Face recognition is a kind of important biological recognition technology, which is applied widely in the public security monitoring, identification, entrance guard system, and other fields. For this technology, features extraction and face classifier design is the key that can directly affect the face recognition results, therefore, the accurate extraction of facial feature and high performance classifier design is crucial to improve the human face recognition [1].

There are mainly local binary pattern (LBP), Gabor and other facial feature extraction methods, which can better describes the face feature to get good recognition effect [2]. But in practical applications, the face image is affected by illumination, expression, age, posture and other factors, LBP can only extract the spatial features of face image and Gabor can only extract the time domain features of face image, therefore, for face recognition under complex environment, the recognition rate of human face based on single LBP, Gabor feature will fall sharply [3]. In recent years, some scholars proposed face recognition methods based on combination features, comparing with the single feature, combined features can realize the complementary advantages to obtain the better effect of face recognition[4-6].Canonical correlation analysis (CCA) can extract the correlation features as discriminant information, achieving the goal of information fusion, but CCA cannot extract the nonlinear relationship between different features, and the kernel canonical correlation analysis (KCCA) is nonlinear extension of CCA. It maps the image features to the kernel space through kernel function and extract the features through this kernel space to get the classification features with more discrimination [7]. For the classifier issues of face recognition, scholars put forward to construct the classifier based on K nearest neighbor (KNN), support vector machine (SVM), neural network classifier to build [8-10].When face image differences are clear between categories, KNN can get ideal identification results, but when the images differences are small, the recognition rate

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falls sharply. SVM overcomes the defects of neural network and the identifying performance is better than other algorithms to construct a classifier, but its training speed is slow that affects the real-time face recognition.

In order to improve the accuracy and efficiency of face recognition, combining with the advantages of multiple features and classifiers, features combination face recognition method (KCCA - MF) based on kernel canonical correlation analysis is proposed. The effectiveness of KCCA-MF is tested through the simulation test.

2. Face Recognition Framework of KCCA-MF

The face recognition based on KCCA - MF includes face image preprocessing, face feature extraction and selection, face combination recognition and other modules, and the concrete framework is shown in Figure 1.

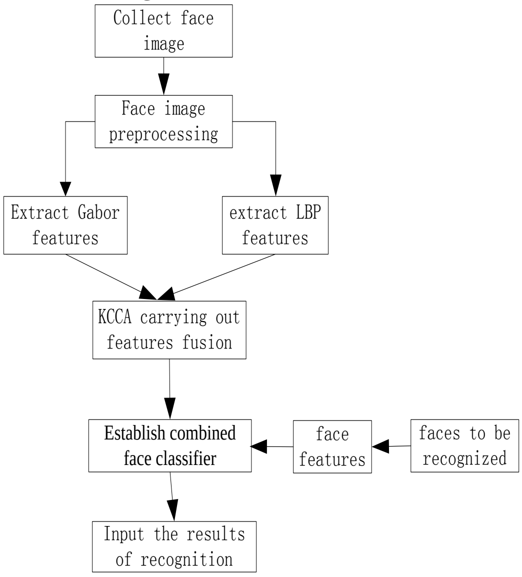

Figure 1. Face Recognition Framework of KCCA-MF

3. Face Recognition of KCCA-MF

3.1. Extract Face Features

(1) Gabor Features

Gabor filer can extract the spatial frequency and local structure features of face image.

$$\psi_{u,v}(z)=\frac{\left\|k_{u,v}\right\|^2}{\sigma^2}e^{-\frac{\left\|k_{u,v}\right\|^2(x^2+y^2)}{2\sigma^2}}(e^{ik\begin{pmatrix}x\\y\end{pmatrix}}-e^{-\frac{\sigma^2}{2}}) \quad (1)$$

The function expression of 2D Gabor filer is $K_{u,v}=\begin{pmatrix}k_x\\k_y\end{pmatrix}=\begin{pmatrix}k_v\cos\varphi_u\\k_v\sin\varphi_u\end{pmatrix}$; σ is the width and wave length ration of Gauss window; X=[x,y] is the location coordinate of spatial domain pixel; ||·|| refers to in modular arithmetic; u and v are the direction and scale of the filter[11].

Take convolution for face image $I(z)=I(x,y)$ and Gabor filter and get the filtering result.

$$G_{u,v}(z)=I(z)*\psi_{u,v}(z) \quad (2)$$

Select 5 scales and Gabor filter groups in 8 directions to get 40 subband outputs. The filtering results in all scales and directions are connected to form a column vector:

$$\chi = \left[g_{0,0}^{T}, g_{0,1}^{T}, \cdots, g_{4,7}^{T} \right]^{T} \tag{3}$$

For the face with size of 128×128, the Gabor feature can reach 655360 dimensions, and it's a high-dimensional feature vector, which will take adverse effect for the reality of face recognition. Therefore, in this paper, we sample subbands for ρ times and then connect all the subbands to get the Gabor feature vector:

$$\chi^{(\rho)} = \left[g^{(\rho)T}{}_{0,0}, g^{(\rho)T}{}_{0,1}, \cdots, g^{(\rho)T}{}_{4,7} \right]^{T} \tag{4}$$

(2) LBP Feature

LBP algorithm is a kind of face feature extraction method proposed by Ojala *et al*. It can describe the changing conditions of the pixels grey level in the domain comparing with the central point. For face image extraction LBP_R^{u2}, take histogram as the spatial features of the image. Due to too big neighborhood, the difference between the pixels in the neighborhood and the central pixels is big, so 3×3 neighborhood is selected and the definition of LBP_R^{u2} is as following: $LBP_3^{u2} = \begin{cases} \sum_{i=0}^{7} s(g_i - g_c)2^i, & U(LBP_3) \le 2 \\ 256, & \text{otherwise} \end{cases}$

In which,

$$s(g_i - g_c) = \begin{cases} 1, & g_i - g_c \ge 0 \\ 0, & g_i - g_c < 0 \end{cases} \tag{5}$$

$$U(LBP_3) = \left| s(g_7 - g_c) - s(g_0 - g_c) \right| + \sum_{i=1}^{7} | s(g_i - g_c) - s(g_{i-1} - g_c) |. \tag{6}$$

In the formula, g_c is the grey value of a central pixel point in a neighborhood; g_i is the grey value of the pixels along clockwise direction of 3×3 neighborhood taking g_c as the center.

3.2. Fuse the Features by KCCA

Get the Gabor features and LBP features of face images with the methods aforesaid, the features dimension is high with redundancy among features, so kernel canonical correlation (KCCA) is used for dimensionality reduction. Set $X=(x_1,x_2,\ldots,x_N)$ and $Y=(y_1,y_2,\ldots,y_N)$ for the vectors of Gabor and LBP features. The kernel functions are k_x and k_y and the kernel matrix as following:

$$\begin{cases} K_X = \Phi^T(X)\Phi(\mathrm{X}) \\ K_Y = \Psi^T(Y)\Psi(\mathrm{Y}) \end{cases} \tag{7}$$

Make zero mean normalization for the training samples:

$$\overline{K} = K - \frac{1}{N} 1_{N\times N} K - \frac{1}{N} K 1_{N\times N} + \frac{1}{N^2} 1_{N\times N} K 1_{N\times N} \tag{8}$$

The target of KCCA is to search for the projection directions α_ϕ and β_Ψ, to maximize the following criterion Function (9)

$$J(\alpha_\Phi, \beta_\Psi) = \frac{\alpha_\Phi{}^T \Phi(X)\Psi(Y)^T \beta_\Psi}{\sqrt{\alpha_\Phi{}^T \Phi(X)\Phi(X)^T \alpha_\Phi \cdot \beta_\Psi{}^T \Psi(Y)\Psi(Y)^T \beta_\Psi}} \tag{9}$$

Vector α_ϕ is the space spanned in samples $\Phi(x_1),\Phi(x_2),\cdots,\Phi(x_N)$. According to the kernel reproducing theory, there will be a N dimensional vector ξ making $\alpha_\phi=\Phi(X)\xi$; in a similar way, there will be N dimensional vector η to make $\beta_\Psi=\Psi(Y)\eta$, substituted into (10) to get:

$$J(\xi,\eta)=\frac{\xi^T K_X K_Y \eta}{\sqrt{\xi^T K_X^2 \xi \cdot \eta^T K_Y^2 \eta}} \tag{10}$$

KCCA is transformed to the constraint optimization problem about ξ, η, and the target function as:

$$\max \xi^T K_X K_Y \eta \tag{11}$$

The constraint condition as:

$$\begin{cases} \xi^T((1-\tau)K_X^2+\tau K_X)\xi=1 \\ \eta^T((1-\tau)K_Y^2+\tau K_Y)\eta=1 \end{cases} \tag{12}$$

Use lagrangian multiplier to solve the extreme value of the band constraint aforesaid, and the related lagrangian equation should be:

$$L(\xi,\eta)=\xi^T K_X K_Y \eta-\frac{\lambda_1}{2}(\xi^T((1-\tau)K_X^2+\tau K_X)\xi-1)-\frac{\lambda_2}{2}(\eta^T((1-\tau)K_Y^2+\tau K_Y)\eta-1) \tag{13}$$

In the formula, λ_1 and λ_2 are the lagrangian multipliers.

Get the partial derivative of $L(\xi,\eta)$ in regard to ξ, η and let it be 0

$$\begin{cases} \frac{\partial L}{\partial \xi}=K_X K_Y \eta-\lambda_1((1-\tau)K_X^2+\tau K_X)\xi=0 \\ \frac{\partial L}{\partial \eta}=K_Y K_X \xi-\lambda_2((1-\tau)K_Y^2+\tau K_Y)\eta=0 \end{cases} \tag{14}$$

Thus, KCCA is equivalent to solve the corresponding feature vector problems of the generalized equation

$$\begin{cases} K_X K_Y \eta=((1-\tau)K_X^2+\tau K_X)\xi \\ K_Y K_X \xi=((1-\tau)K_Y^2+\tau K_Y)\eta \end{cases} \tag{15}$$

Get ξ, η, and extract the non-linear relating features between x and y.

$$\begin{cases} u=\xi K_X \\ \text{v}=\eta K_Y \end{cases} \tag{16}$$

In the formula, u, v are the feature vectors after transformation.

3.3. Construct the Combined Classifier of Face Recognition

(1) Support Vector Machine

Given $\{x_i,y_i\}$, $x_i \in R^n$, i=1,2,…,l, l refers to the samples quantity. According to the risk minimization principle, SVM is to find the best optimal hyperplane to divide the training data into two classifications. The hyperplane is to solve into the following formula through the convex quadratic programming problem below (for details, see the literature [12])

$$\max \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \alpha_i y_i \alpha_j y_j K(x_i, x_j) \tag{17}$$

$$s.t. \begin{cases} \sum_{i=1}^{l} \alpha_i y_i = 0 \\ C \geq \alpha_i \geq 0 \\ i = 1, 2, \cdots l \end{cases}$$

In the formula, α_i refers to the multiplier of Lagrange; C refers to penalty coefficient; $K(x_i,x_j)$ refers to the kernel function.

Given a test case x, SVM classification decision function is

$$f(x) = sgn(\sum_{x_i \in sv} \alpha_i y_i K(x_i, x) + b) \tag{18}$$

In the formula, b is the sorting threshold; sv is the supporting vector.

$$k(x, x_i) = \exp\left(-\frac{\|x - x_i\|}{2\sigma^2} \right) \tag{19}$$

(2) K-nearest Neighbor Algorithm

K-nearest neighbor algorithm (KNN) is a kind of important recognition method for non-parametric model. It selects K neighbors of the unknown sample x then attribute x to one classification of the neighbor of K.

(3) Combined Classifier

For the face sampling points of hyperplane border region, the SVM can't properly identify; however, KNN cannot recognize face image of the classifications with great difference, therefore, take advantage of KNN and SVM as complementary, overcome their own shortcomings, to build a combination face image classifier, and the specific idea is: when the distance between the faces to be recognized and the optimal hyperplane is greater than the pre-set threshold, using SVM to recognize; Otherwise using support vector point of KNN for face image recognition, as shown in Figure 2.

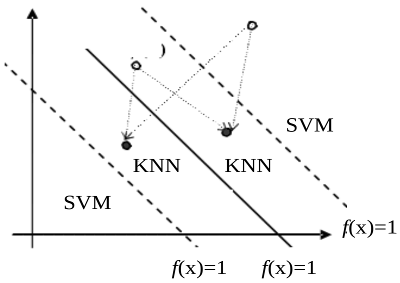

Figure 2. Face Recognition Diagram of Combined Classifier

3.3. Analysis of Time Complexity

Assume there are two kinds of sample data and N samples. The quantity of each sample is N_1,N_2, and two random samples complexity is denoted as 1. KNN needs to calculate the distance between each sample and other sample points, so the calculated complexity is $O((N_1+N_2)(N_1+N_2-1) \approx O(N^2)$; the time complexity of SVM is $O(N^3)$; the samples laid on the optical hyperplane only take up small part, therefore, comparing to KNN and SVM, the calculating quantity of KNN-SVM is less. And the calculating complexity is also reduced.

3.Simulating experiment

3.1Data source

Use the standard face database Yale、ORL、FERET as the simulation objects. These face databases cover the face images under various conditions[13]. KCCA selects radial basis kernel function, and the kernel parameter σ=0.8, the parameter of SVM C=100，σ=1.25, K value of KNN is 3.

3.4. Results and Analysis

(1)Yale face database

There are 15 persons in Yale face database. Each one has 11 images with size of 243×320 under 3 kinds of different illuminations, with 6 different expressions, distinguished with glasses and without glasses. Some Yale face images area shown as Figure 3:

Figure 3. Some Face Image Samples in Yale

Select M=3,4,5 randomly as the training set. The rest face images are taken as test set. Under the fixed training sample quantity M each time, repeat the experiment for 10 times and take the average value of the results. The single Gabor feature, LBP feature, traditional combined feature (Gabor and LBP feature, no KCCA fusion), the face recognition methods of literature [14-15] and the recognition rate of KCCA-MF is shown in Figure 4. Use single KNN and SVM for comparison experiment, and the recognition rate and time are shown in Table 1.

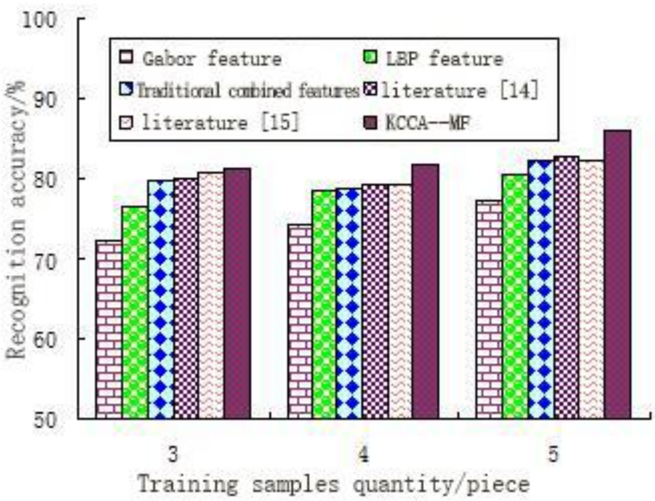

Figure 4. Yale Face Database Recognition Results of Different Extraction Methods

Table 1. Yale Face Database Recognition Performance Comparison of Different Classifiers

Method	3	4	5	Running time (s)
KNN	68.90	73.28	75.59	0.79
SVM	75.12	77.45	80.27	2.55
KCCA-MF	78.45	80.71	84.98	0.66

To analyze the results of Figure 4 and Table 1, we can conclude as following:

（a）Comparing with the face recognition methods of single Gabor feature, LBP feature, KCCA-MF increases the face recognition rate greatly. Because KCCA-MF combined the time and spatial features of face images, realizing complementary, describing the classified information of face images better.

(b)Compared with the traditional combined features face recognition method, the recognition rate of KCCA - MF is higher, mainly due to the redundant among the traditional combined features is serious, harmful to identify, and KCCA - MF eliminates the redundant features by KCCA, having important influence to the recognition result of feature extracting, and when the external environment change greatly, it has better robustness.

(c)Compared with the classical face method, KCCA - MF face recognition accuracy is slightly increased, indicating that KCCA - MF fusing features and classifiers from two aspects, impring the whole performance of face recognition with certain advantages.

(d)Compared with the single KNN and SVM classifier face recognition method, KCCA - MF method improves the face recognition rate, mainly due to the KCCA - MF fully mixing the advantages of SVM and KNN, overcoming the defects of a single SVM and KNN, and accelerating the speed of face recognition that can satisfy the real-time requirement of face recognition.

(2)ORL Face Database

ORL face database contains 40 kinds of face image, each kind with l0 images, and part of the ORL face images are shown in Figure 5.Sselect (M =3,4,5) face images as the training sample, the rest is used for test, and the recognition effect of different feature extraction methods for ORL face database is shown in Figure 6.ORL face recognition results of different classifier databases are shown in Table 2.From figure 6 we can see that compared with the contrast method, KCCA - MF method recognition rate increases to some extent. From Table 2, relative to the single KNN and SVM, KCCA - MF method has better effect for face recognition.

Figure 5. Some Face Images of ORL

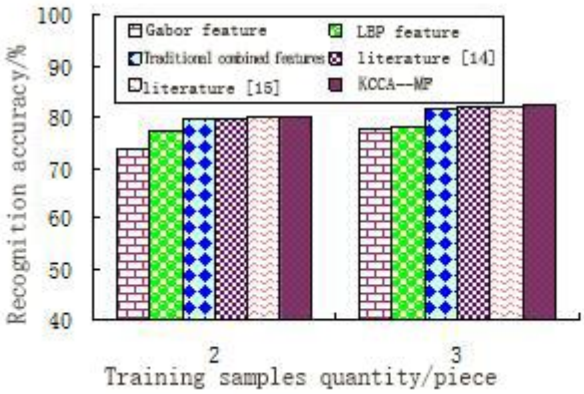

Figure 6. ORL Face Database Recognition Results of Different Extraction Methods

Table 2. ORL Face Database Recognition Performance Comparison of Different Classifiers

Method	3	4	5	Running time (s)
KNN	78.16	77.65	80.92	0.83
SVM	88.12	87.85	90.45	2.58
KCCA-MF	92.15	94.16	95.13	0.72

(3)FERFET face database

Because the FERET face database is big, so select 120 persons randomly and each one has 6 images including different expressions, postures, ages and illuminations, as shown in Figure 7. Select (M =3,4,5) face images as the training sample, the rest is used for test, and the recognition effect of different feature extraction methods for FERET face database is shown in Figure 8.

Figure 7. Face Images from FERET Face Database

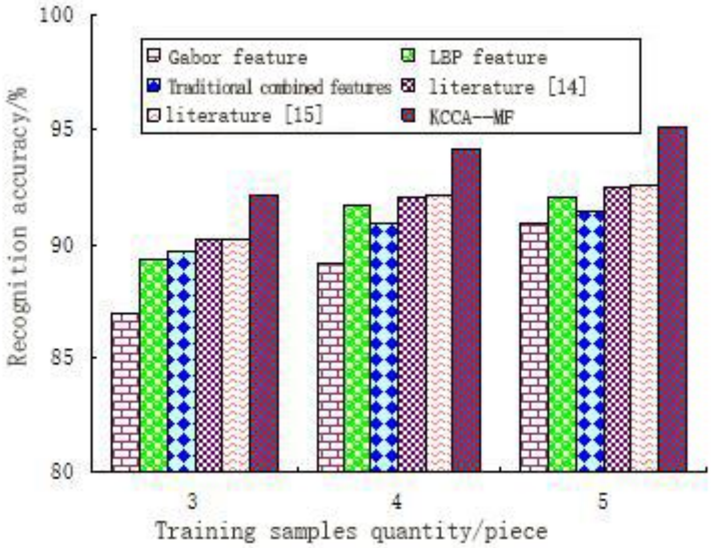

Figure 8. FERET Face Database Recognition Results of Different Extraction Methods

According to the experimental results in the Figure 8, with training samples increasing, the recognition rate of various methods needs to be improved. Under the condition of the same training sample number, KCCA - MF is a mixture of the Gabor, LBP features that can describe face images from different aspects, and use KCCA to integrate the image information, to obtain the better features. The recognition performance is superior to contrast methods with more robust regarding illumination, expression change.

Table 3 shows that under the same dimension conditions, the face recognition accuracy and speed of KNN, SVM, and KCCA - MF, from table 3, KCCA - MF recognition rate is far higher than the contrast methods, and obtains a faster recognition speed, which indicates the effectiveness and superiority of KCCA - MF.

Table 3. FERET Face Database Recognition Performance Comparison of Different Classifiers

Method	2	3	Running time (s)
KNN	70.15	71.47	0.95
SVM	75.19	77.30	3.22
KCCA-MF	80.12	82.25	0.80

4. Conclusion

The paper puts forward a kind of KCCA - MF method for face recognition according to the feature and classifier building problems in the process of face recognition. Results show that KCCA - MF can obtain higher stability for its local change of shade, illumination, expression by the different features of KCCA fusion images. At the same time, using the combined human face classifier composed by KNN and SVM improves face recognition rate and robustness. However, the parameters of SVM and K value of KNN influence face recognition rate in a certain degree. It will be the research direction for the next step to find better SVM parameters and K value and improve the effect of face recognition further.

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