Ethnic Features Extraction and Recognition of Human Faces

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Abstract—Ethnic Facial Feature is one of the most important face features. We create a face database of ethnic groups and extract facial features by using face recognition technology. In the feature extraction method, we adapt the algebra and geometry features from face database. In algebra features, LDA algorithm extracting the algebraic features of human face images is used. The paper also constructs a new face template to extract the geometric features and locates the points of face templates by using Gabor Wavelet. KNN and C5.0 Classifiers are used to learn the train dataset. The result indicates that the average recognition accuracy rates of Tibetan, Uighur and Zhuang ethnic groups can reach 79% by algebraic features and 90.95% by geometry features.

Keywords Minority characters of face, Face recognition, LDA, PCA, Gabor Wavelet, Minority recognition

I. INTRODUCTION

The research of the ethnic facial feature is of great significance for the science and technology and national unity. It is well known that China is a multi-ethnic country in which all the ethnic groups are interacted and merged with each other in thousands of years. Meanwhile, the facial features of each ethnic group are changing. In the progress of national integration, the national facial features has not disappeared, but evolved with new features. It is of the practical significance for the protection of ethnic cultures and the research of the development process to digitalize the preservation of ethnic culture and to study and find the new features produced in the ethnic merges.

Ethnic facial featu re is another important characteristic expressing facial information besides gender, age, and emotion. The relevant research is a useful complement and enriches face recognition technology. The research shows that there are differences between different ethnic groups in face characteristics. Differences maybe exit even in the same ethnic group due to the different areas. As shown in table 1, some national face features of the three related ethnic groups *are given in the paper*[1, 2, 3].

The research of ethnic facial feature extraction and recognition is still relatively rare in the world. At present, Shakhnarovich[4] *used boosting algorithm to recognize and classify Asians and non-Asians. Xiaoguang Lu and Anil K. Jain*[5] *used LDA technology to do multi-dimension facial features extraction and the nearest neighbor classification to classify the Asians and non-Asians. Satoshi Hosoi and Erina Takikawa*[6] *combined Gabor Wavelets Transformation and retina sampling to extract key facial features and used support vector machines for ethnicity classification.*

Table 1 the different ethnic Minorities facial features in China

Minority	*Facial characteristics*
Tibetan	*Eye：midium rima oculi opening, apparent inner wrinkle* *Nose：straight, fine, high nasion* *Lips：convex，medium thick，lower lip is thicker than upper lip* *Face shape：long shuttle type* *Hair：straight or slightly wavy* *Ear：Darwinian tubercle appears in the upper part, circular earlobe*
Uighur	*Eye：wedge-shaped structure，apparent upper eyelid folds，* *Nose：medium high nasion, high tip of the nose* *Lips：thin , the location of the upper lip is a little high* *Face shape：oval* *Hair：wavy, curly or straight* *Ear：Darwinian tubercle, circular or square earlobe*
Zhuang	*Eye：wide rima oculi opening, micro-displayed Mongolian fold* *Nose：convex in lower bridge, concave in upper* *Lips：medium high nasion, apparently convex,* *Face shape：wide face* *Ear：no Darwinian tubercle,*

These researches focused on several key races in the world, but related study on different minorities in the same race is relatively rare home and abroad. The facial features research did not gain the general concern from the country and the society until 1990s in China. However, experts and

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scholars are more concerned about Han group rather than other ethnic minorities.

II. ETHNIC FACIAL FEATURE EXTRACTION

In this paper we will extract two features from the dataset: geometric feature and algebraic feature. First we will do image pre-processing, then use LDA algorithm to extract the algebraic features and ethnic facial flexible template to extract geometrical features.

A. Image pre-processing

The first step we should do is image pre-processing with the ethnic face database. The aim of this step is to remove the noise in the image and strengthen the ethnic feature information in order to facilitate feature extraction and recognition. Here gray-scale transformation and geometry transformation will be used in the image pre-processing. Gray-scale transformation means image gray-scale equalization and removing of the background that can affect the image quality. Geometry transformation means image size normalization and posture correction. Here size normalization is uniform the size of the image scale in order to guarantee the translation and scale invariance and correct the posture in order that the human face eyes center on the same straight line.

Tab.2 The average and standard deviation of several face characters

M	sex	Eye width		Mouth width		Face width		Nose width	
		AVG.	stdev	AVG.	stdev	AVG.	stdev	AVG.	stdev
T	Ma	0.477	3.3	0.654	3.6	1.85	9.1	0.864	1.8
	F	0.485	0.77	0.701	3.7	1.91	7.7	0.869	3.6
U	Ma	0.518	3.6	0.719	7.5	1.98	14.	0.845	5.9
	F	0.502	2.6	0.679	5.0	1.95	13.	0.866	6.7
Z	Ma	0.491	1.7	0.702	5.4	1.98	7.0	0.821	5.5
	F	0.487	1.4	0.702	5.3	2.03	11.	0.859	5.9
AVG.		0.493	2.23	0.693	5.08	1.95	10.3	0.85	4.90

Here in table 2, M represents Minority, T represents Tibetan, U represents Uighur, Z represents Zhuang, stdev represent standard deviation, AVG. represents average, F represents female, Ma represents male.

We consider the mean of eye width as normalize basis vector to do equal proportion transformation with the images. As shown in table 2, relative variance of eye width differences is the minimum; it is 2.23×10^{-3}. After normalization the feature vectors have properties as size, displacement, rotation invariance, so it can contribute to an accurate classification and identification.

B. Algebraic features extraction based on LDA algorithm

Linear Discriminant Analysis (LDA)[7] is a well-known statistical method to project the given multi-dimensional data to a lower dimension such that the ratio of between-class scatter to with-in class scatter is maximized.

Assume there are N images in the original image database, and n pixels in each image. All images are classified c classes, and the number of samples in every class is N_i. The average facial image of all the classes is:

$$m_i = \frac{1}{N_i}\sum_{j=1}^{N_i} x_{ij} \tag{1}$$

Here, x_{ij} means the j_{th} facial sample in the i_{th} class.

The mean of general face is:

$$m = \frac{1}{N_i}\sum_{i=1}^{c}\sum_{j=1}^{N_i} x_{ij} \tag{2}$$

Then we can get divergence matrix between-in class and with-in class of the face samples seeing as follows:

$$S_B = \sum_{i=1}^{c} N_i (m_i - m)(m_i - m)^T \tag{3}$$

$$S_W = \sum_{i=1}^{c}\sum_{j=1}^{N_i} (x_{ij} - m_i)(x_{ij} - m_i)^T \tag{4}$$

The target of algorithm LDA is finding the best projection:：

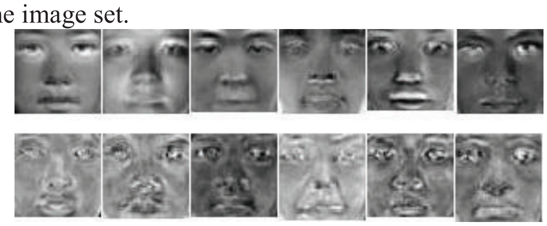
$$W_{opt} = \arg\max \left| \frac{W^T S_B W}{W^T S_W W} \right| = [w_1, w_2, \cdots, w_m] 。$$

If S_W is nonsingular, then $\{w_i \mid i = 1, 2, \cdots, m\}$ is feature vectors corresponding to the m Maximal Eigen values $\{\lambda_i \mid i = 1, 2, \cdots, m\}$ which are satisfied with (5).

$$S_B W_i = \lambda_i S_W W_i, i = 1, 2, \cdots, m \tag{5}$$

We consider face images belongs to the same minority a class. Given c ethnic groups belonging to the N pieces of face image training samples, due to at most the rank of S_w is N-c, and the number of training samples is generally less than the dimension of human face images, so S_w is often singular. We will reduce the dimension to *N-c to make the* S_w non-singular with the PCA[8] algorithm before the using of LDA algorithm for feature extraction.

As shown in figure 3 are the images of the training samples' feature vectors. From it we can see that the first few feature vectors corresponding to the large Eigen values are rich in human face information, while those corresponding to the smaller Eigen values reflect the noise in the image set.



(a)The 6 frontal characteristic vector images (b) the latter 6 characteristic vector images

Fig 2 The images filtered by PCA

Concrete steps are as follows:

(1) Calculating the mean of all the ethnic groups' face images according to equation (1);

(2) Calculating the total average of the images according to equation (2)

(3) Using PCA algorithm to reduce the dimension.

(4) Calculating the divergence matrix between-in class S_b and with-in *class* S_w according to equation (3) and (4).

(5) According to equation (5), calculate the generalized Eigen values and eigenvectors;

(6) Arranging generalized Eigen values in decreasing order. The top d Eigen values corresponding to a larger feature vector composed of feature space;

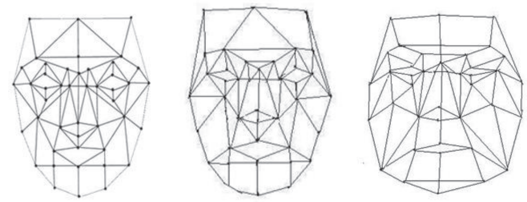
(7) To project each face image to the above feature space, we can get a set of coordinates which correspond to the points in the sub-space. The following vector that $y_i=W_f\ x_i$, y_i is feature describing of the d dimensions vector inputted in face x_i, it can be used in the image space to restore the original images or as face features extracted for classification and identification.

C. Extract geometrical features by elastic model of ethnic features

According to prior knowledge of facial topological structure and geometrical relationship in all ethnic groups, Face Recognition of Ethnic Group based on geometrical features extracts facial features of all ethnic groups by using the Structure-based approach on the knowledge level. Usually, geometrical features contain the position of the main facial feature points, angle, curvature, Euclidean distance or other Features between two designed points. From such features can we obtain Eigenvector of each face. Then we can express one face by a set of geometrical eigenvector. It requires that the geometrical eigenvector chosen has a certain specificity. Not only will it reflect the disparities among different ethnic groups, but also it should possess a certain flexibility, so as to eliminate affects caused by illumination, posture and others.

Relevant anthropological research shows that ethnic minorities have many distinct facial features, such as major axis of eye and eyebrow, and angles between them (Major axis of eyebrow is one line linked two lowest points of the eyebrow. and major axis of eye is another line linked medial canthus and external canthus. For example: these two lines of Mongolian and Tibetan are always parallel and intersectant outside the face. But to Uygur they are often parallel and intersectant in the nasion zone). Meanwhile, there are significant differences in the height, position and shape of the nose from the profile among different nations[9].

This research extracts features using the elastic template. But due to the disparities between national features and traditional ones, it needs us to construct national elastic template which is different from the routine template. After ethnic features are introduced to the template (Fig.3), the elastic templates of all ethnic groups are well established. And features differ obviously among groups.



(a)Uygur (b) Tibetan (c) Zhuang

Fig. 3 The elastic template of different minorities

A part of samples are selected firstly in this paper, and then the position of each feature point is Manual calibrated in the elastic template. Since the Gabor wavelets[10] coefficients are realized by computing the convolution s of the Gabor wavelets filters in a set of different center frequencies and directions and the grey values of pixels in an area around a given position in an image, this kind of representation has the merit of insensitiveness to the location and illumination. So in this paper we use Gabor wavelets[11][12] to extract veins information in diverse frequencies and directions in an area around the feature points in the picture. As shown in figure 4, we establish relations between facial feature points and the corresponding features in the elastic template, and extract geometrical features which can describe the topological relationship of all facial organs.

In the preprocessing of face image, we ensure all the feature points cover the face area relatively uniform. Then through elastic bunch graph matching the location of basic feature points in Fig 3 can be fixed on by using the wavelets. And eyebrow, eye, nose, mouth, face contour are firstly chosen as the basic points. Other feature points will be obtained by calculating the average position of several basic points. And they are named derived feature points.

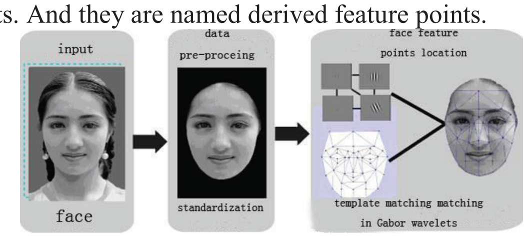


Fig 4. The processing of locate the template by Gabor Wavelet

After locating the feature points, we extract the coordinates of them in the template. And relevant software is developed in this paper (Fig 5). Then elastic templates of the samples in the image database are stored in the model file. Now we can compute the proposition and angle of many ethnic features by using the information of the template.

Fig. 5 The software for minority face recognition &.model files

III. EXPERIMENTS AND ANALYSIS

In this paper, we choose Tibetan, Uygur, Zhuang in the image database as our research object. After extracting the geometrical and algebraic features of the image database, we divide the data set into training set and test set. In order to validate the respective recognition results of these two features, we carry out this experiment.

A. Experiments and results of algebraic features

We extract features from the samples though LDA method, and get the ultimate representation to the character of the image. Because numerical vectors are extracted by algebraic features, we use KNN classifier to make predictions to the test. Euclidean distance is regarded as the distance function in KNN algorithm.

The recognition accuracy of KNN algorithm [13][14] depends on the value of K. and in the experiment we find out when K=5. It achieves the best result. Totally we carry out 10 times experiments. In order to prevent the results toward to any race, the number of training datasets for each category is the same. Then from the three ethnic groups we extract one sample randomly with the capacity of 150 as one racial training datasets, and extract 70 as our test set in the remain ones. The average recognition accuracy is shown in Tab 2. The bold describes the correct recognition rate.

Tab.2 The recognition results of algebraic features

Data set	Test result		
	Tibetan	Uygur	Zhuang
Tibetan set	0.771429	0.142857	0.085714
Uygur set	0.157143	0.785714	0.057143
Zhuang set	0.114286	0.071429	0.814286

The result shows that, the correct recognition rate of Tibetan reaches to 77.1%,the wrong rate of Tibetan which is identified as Uygur is 14.2%, and wrongly classified as Zhuang is 8.5%. The correct recognition rate of Uygur reaches to 78.5%, the wrong rate of Uygur which is identified as Tibetan is 15%, and wrongly classified as Zhuang is 5.7%. Finally, the correct recognition rate of Zhuang reaches to 81.4%, the wrong rate of Zhuang which is identified as Tibetan is 11.4%, and wrongly classified as Uygur is 7.1%.and the average recognition rate is 79%.

B. Experiments and Results of Geometyical Features

First, preprocessing is performed to the extracted information of face template, and computing the relevant nationality character. Then from the three ethnic groups we extract one sample randomly with the capacity of 150 as one racial training datasets, and extract 70 as our test set in the remain ones.

To acquire the final classification rules, C 5.0 is adopted as the training algorithm to make leaning to the training set[15][16][17]. Grain ratio is employed to weigh the breath and evenness of attribute partitioning data by C 5.0 algorithm, Decision tree is constructed and synthesis entropy is applied to weigh the Grain ratio.

The arithmetic process is as follows:

Theorem 1: Supposing S is a data set, $\{C_1,C_2,......,Cm\}$is the class collection contained in S, Let $P(S_c)$ express the probability of class C appears in S.

Theorem 2: Suppose $\{a_1, a_2,..., a_V\}$are different values of attribute A,S is divided into V subsets $\{S_1,S_2,..., S_V\}$according to attribute A. and $|S_V|$ represents the sum of each sample in subset$\{S_1,S_2,...,S_V\}$.|S| is the total number of samples in S.

Step1. Compute Information Entropy $E(S)$ and measure the disorder degree,

$$E(S) = -\sum_{i=1}^{m} P(S_c)\times \log_2 P(S_c) \tag{6}$$

Step2. Compute Information Gain, which is used to measure the result of ordinal improved.

$$Gain(S,V) = E(S) - \sum_{V\in Values(V)} \frac{|S_V|}{|S|}\times E(S_V) \tag{7}$$

Step3.There are deviations of attribute A in Information Gain which is applied to divide the data set into smaller ordered subsets. In order to reduce deviation, SplitInfor are used to compute entropy of each variable relative to its m values of variables.

$$SplitInfor(S,V) = \sum_{V\in Values(V)} -\frac{|S_i|}{|S|}\times \log_2 \frac{|S_i|}{|S|} \tag{8}$$

Step4.Gain ratio is calculated by the following formulate which can reduce deviation of large value dataset.

$$GainRatio(S,V) = \frac{Gain(S,V)}{SplitInfor(S,V)} \tag{9}$$

C5.0 algorithm is used to make learning to the training set. And parts of the rules are shown as follows:

Rule 1 – rule accuracy 90% nose width <= 0.589 [category: Tibetan] => Tibetan

nose width > 0.589 [category: Uygur]

length from angulus oris to ipsilateral medial canthus <= 2.030 [category: Zhuang] => Zhuang

length from angulus oris to ipsilateral medial canthus > 2.030 [category: Uygur]

face width on the line of nasal-alar <= 4.462 [category: Uygur]

mouth width <= 1.481 [category: Tibetan] => Tibetan

mouth width > 1.481 [category: Uygur] => Uygur

face width on the line of nasal-alar > 4.462 [category: Zhuang] => Zhuang

rule 2 – rule accuracy 72.59%

length from chin to corner of mouth <= 1.526 [category: Zhuang]

length from chin to tip of nose <= 1.913 [category: Tibetan] => Tibetan length from chin to tip of nose > 1.913 [category: Zhuang] => Zhuang

length from chin to corner of mouth > 1.526 [category: Uygur]

face width on the line of nasal-alar <= 4.220 [category: Uygur] => Uygur

face width on the line of nasal-alar > 4.220 [category: Tibetan] => Tibetan

rule 3 – rule accuracy 87.18%

length from angulus oris to ipsilateral medial canthus <= 2.030 [category: Zhuang]

length from chin to tip of nose <= 1.863 [category: Tibetan] => Tibetan

length from chin to tip of nose > 1.863 [category: Zhuang] => Zhuang

length from angulus oris to ipsilateral medial canthus > 2.030 [category: Uygur]

length from nosetril to ipsilateral angulus oris <= 0.797 [category: Tibetan] => Tibetan

length from nosetril to ipsilateral angulus oris > 0.797 [category: Uygur]

right-eye width <= 0.962 [category: Uygur] => Uygur

right-eye width > 0.962 [category: Tibetan]

face width on the line of nasal-alar <= 4.089 [category: Tibetan] => Tibetan

face width on the line of nasal-alar > 4.089 [category: Zhuang] => Zhuang

rule 4 – rule accuracy 86.95%

nose width <= 0.589 [category: Tibetan] => Tibetan

nose width > 0.589 [category: Zhuang]

nose width <= 0.733 [category: Uygur]

length from angulus oris to ipsilateral medial canthus <= 2.030 [category: Zhuang] => Zhuang

length from angulus oris to ipsilateral medial canthus > 2.030 [category: Uygur]

face width on the line of nasal-alar <= 4.462 [category: Uygur] => Uygur

face width on the line of nasal-alar > 4.462 [category: Zhuang] => Zhuang

nose width > 0.733 [category: Tibetan] => Tibetan

With these rules, we make classification predictions to the test set. And the final results are shown in Tab3.

Tab.3 The recognition results of geometry features

Data set	Test result		
	Tibetan	Uygur	Zhuang
Tibetan set	0.885714	0.071429	0.042857
Uygur set	0.071429	0.900000	0.028571
Zhuang set	0.042857	0.014286	0.942857

The result shows that, the correct recognition rate of Tibetan reaches to 88.6%, the wrong rate of Tibetan which is identified as Uygur is 7.1%, and wrongly classified as Zhuang is 4.3%.and the correct recognition rate of Uygur reaches to 90.0%, the wrong rate of Uygur which is identified as Tibetan is 7.1%, and wrongly classified as Zhuang is 2.8%. Finally, the correct recognition rate of Zhuang reaches to 94.3%, the wrong rate of Zhuang which is identified as Tibetan is 4.2%, and wrongly classified as Uygur is 1.4%.and the average recognition rate is 90.95%.

C. *Experiment analysis*

The results of Tab1 show that the face of all ethnic groups is separable on the basis of algebraic features, and a certain of character crossover existed in each ethnic group. Then we can find out LDA+KNN method has a strong discrimination ability to the classification of ethnic groups.

And Tab2 reveals that the recognition accuracy of geometrical features is higher than the algebraic ones. Thus, geometrical discrimination is far higher than algebraic discrimination in ethnic features of human’s face.

IV. CONCLUSION AND PROSPECT

Ethnic features of human’s face are researched by extracting geometrical and algebraic features of all ethnic groups in this paper. First, Algebraic features are extracted by LDA+PCA method. Then geometrical features are extracted by the relative elastic template which uses Gabor wavelets. And the result shows that all ethnic faces are separable, no matter what they are based on the geometrical discrimination or algebraic discrimination and certain features crossover exist in each ethnic group.

Recognition of ethnic features is significant in addition to the facial recognition, and there is broad prospect in theory research and application. It is meaningful to discern which ethnic or regional features are possessed on the face and distinguish which groups are similar on appearance. Also experiments have testified that the method and technology of the research are feasible. Together with the construction and improvement of facial database, more contents related will be researched. Further more, recognition technology of ethnic facial features can be made as weak classifier to large-scale face searching[18][19][20],which will speed up the matching pace of face recognition system. And this research can be extended to research on ethnic groups of other countries. It will play an important role in national security which is on the background of growing international communication. Meanwhile, it will help us to know about the development situation of all ethnic groups more overall and timely.

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