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ORIGINAL ARTICLE

Facial semantic representation for ethnical Chinese minorities based on geometric similarity

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Abstract Facial semantic feature analysis for ethnical Chinese groups is one of the most significant research topics in face recognition and anthropology. In this paper, we build an ethnical Chinese face database including three ethnical groups, and then manifold learning technique is applied to analyze facial ethnic features for discriminant semantic representation. Firstly, we conduct manifold analysis on the basis of facial geometric indicators that are proposed by anthropologist, which are eventually shown not distinguishable in semantics concepts. Therefore, it is necessary to expand the scope of facial features by calculating the complete distances, angles and indexes associated with landmarks. Then, mRMR-based feature selection is applied to select 2926 distance indicators, more than 210,000 angle indicators and more than 4,100,000 index indicators ethnical feature representation, and 5 datasets with features of distance, angle, index, anthropology and combinations are obtained. Secondly, several popular manifold learning methods, such as LPP, ISOMAP, LE, PCA and LDA are utilized to investigate the ethnic features obtained above, and the results show the distinguishable manifold structure of facial ethnical features and clusters in 4 of the 5 datasets. In order to evaluate the validity of filtered features, the classification algorithms, J48, SVM, RBF Network, Bayesian, and Bayes Network in Weka, are carried out based on the filtered features. The experimental results reveal that the average of classification accuracy on the dataset with combined features is higher than other datasets, and the corresponding indexes are more salient than other geometric features. Finally, the sub-manifold structures with semantic concepts are found based on the ethnic facial data. Facial features of three Chinese ethnic groups exist in different ethnic semantic sub-manifolds in the low-dimensional space. Facial measurement indicators obtained by manifold analysis and feature selection provide not only a method for computational facial ethnic groups analysis, but also an enrichment and improvement to the related research in anthropology.

Keywords Facial ethnic features · Biometrics recognition · Face recognition · Ethnical Chinese groups

1 Introduction

As an important visual information, face plays a key role in reflecting message during the interaction between people. In many practical applications, the vision-based systems are equipped with the capability of accurately recognizing age, expression and gender from face [1–5]. The race, ethnic groups and ethnicity of a face have significant practical values in anthropology, vision-based security, criminal identification and border inspection techniques [6–8]. Meanwhile, the research can promote democratic equality of pattern recognition system for different race, ethnicity and ethnic groups, which can avoid possible "discrimination" [8] caused by system's preference in partial ethnic groups. How to utilize computer techniques to analyze and represent the

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ethnical facial features computationally and mutually can boost face recognition and anthropology research.

Race of people can be distinguished with skin color, hair and body structure from the viewpoint of anthropology. Ethnic group is human group with different custom, appearance characteristic and language. Facial ethnicity is one of the most crucial facial features, which is reflected by the cognitive order of face recognition. As shown in Fig. 1, human firstly recognize the ethnicity of face is processed in the very early stage (80–120 ms) of face interpretation, followed by the cognition of age and gender information (after 150 ms) [9].

Many anthropology researchers have intensively investigated the facial features of different ethnic groups by acquiring numerous data with anthropometric indicators and statistical analysis [10, 11]. Measurement indicators including distances between landmarks and angles are proposed, which significantly promote the development of anthropology. With the increasing development of computer vision and facial analysis techniques, it is very meaningful for the research in the field of anthropology that how to build a more reasonable and all-sided measurement indicators on the basis of raw data. In [12], the authors utilize the distances between facial geometric features and its ratios to investigate the facial features of Caucasian. Kanade [13] conducts an analysis on the relationship among the facial features of canthus, mouth and chin, which are extracted from self-constructed dataset including 20 Caucasians. Brunelli and Poggio [14] investigates the mapping relationship among the geometric structure of facial components (such as the length of nose, the width of mouth and the shape of chin), which find that facial geometric features can be viewed as the evidence of recognizing ethnic groups. Moreover, for an individual's face, it may consist of several ethnic groups' facial features because of integration between ethnicities, which renders the difficulties in analyzing ethnic facial features. Therefore, how to extract and investigate the general ethnic facial features from various individuals is a critical problem.

It is much more difficult to extract and recognize ethnic facial feature from various ethnic groups of the same race than that from diverse races. Facial features of individuals belong to distinct races vary in different skin color and appearances. Generally, a race includes many ethnic groups.

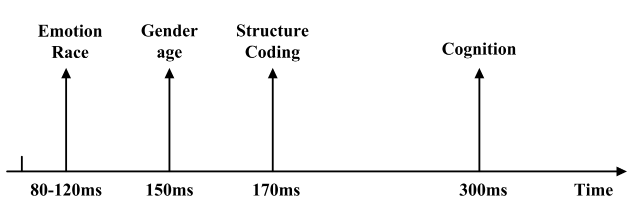


Fig. 1 The cognitive order of face recognizing

The difference between ethnic groups is less significant than that between races [15]. In 1991, Lindsay found that people's memory in the faces of individuals belong the own race is better than that belong other races [16]. The reason for this phenomenon is that people usually contact with individuals belonging to their own race rather than other races. Recently, researchers mainly focus on facial ethnic features of different races, and rare researches involve ethnic groups in specific race. China is a multi-ethnic country, in which many ethnic groups are formed by influence of geography, lifestyle and inheritance during in the long history and living in various areas across five time zones [17]. Hence, the investigation on how to investigate facial ethnic features of ethnic groups in China by computer science is very meaningful.

Manifold learning is a technique which can reveal low-dimensional manifold structure from high-dimensional sampling data space and obtain corresponding mapping at the same time. The method not only reduces high-dimensional data but also visually analyzes the essence of object and investigates the invariant principles in raw data [18]. In 2010, Seung and Lee published 'The manifold ways of perception' on Science, which discusses the visual perception mechanism of human, verified that human's visual system is capable of capturing the non-linear manifold structure and proposed the hypothesis of visual perception [19]. When face image to be recognized under variations of illumination, expression, age and pose, a low-dimensional manifold which is controlled by influence factors will be generated from the high-dimensional space of human vision. However, whether facial ethnic features exist in such a low-dimensional manifold controlled by ethnic features for different individuals remains unknown. In [20], the authors indicated that manifold related research in facial ethnic features is still not be initiated, and data collection should be carried out to analyze the manifold structure of facial ethnic features. In this paper, aiming at the facial feature of Chinese ethnic groups, we have carried out several tentative researches including creating Chinese ethnic face database and investigating the facial features of different ethnic groups, and the resultwhich indicates that different ethnic groups are diverse and distinguishable in facial features [21–23].

This paper discusses the manifold structure of several Chinese ethnic groups' facial features and evaluate the availability of our supplemented indicators, with the purpose of exploring the essential semantics concepts of facial ethnic feature. The rest of the paper is organized as follow. A review of literature is presented in Sect. 2. Section 3 introduces the work on multi-ethnic face data set collection including choosing research subjects, acquisition environment setup and image pre-processing. Section 4 gives the detail of face landmarking and geometric similarity computation followed by the evaluation of anthropological measurement indicators on constructed Chinese ethnic face datasets. We present and analyze the experimental results are presented in Sect. 6 , concluded our work in Sect. 7.

2 Related works

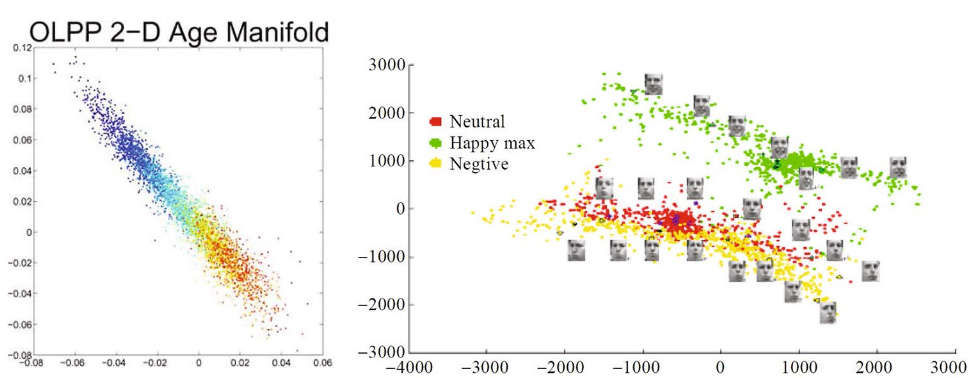
Subspace analysis method in learning low-dimensional manifold from a high-dimensional facial image data is a popular research topic in face recognition and analysis. The main idea of subspace method is structure learning, which intends to find a reliable and reasonable embedded projection. The projection maps original data into low-dimensional subspace. During the transformation, redundant data is reduced in order to obtain the compact representation [18, 24, 25]. Conventional manifold linear subspace algorithms mainly include principle component analysis (PCA) [26], linear discrimination analysis (LDA) [27], independent component analysis (ICA) [28], two-dimension principle component analysis (2D-PCA) [29], two-dimension linear discrimination analysis (2D-LDA) [30], and so on. In [31], the authors proposed local linear embedding (LLE) and isometric feature mapping (ISOMAP). In order to overcome LLE's defect in matrix decomposition and noise data's immunity, Laplacian Eigenmap (LE) is proposed based on the spectral analysis theory [32]. However, non-linear dimension reduction methods like LLE or LE can only obtain low-dimensional embedding of training samples and can not explicitly give the mapping relationship, which leads to difficulty of getting the low-dimensional projection for a new sample. Therefore, [33, 34] proposed the concept of local preserving projections (LPP) which is the linear extension of LE. Because of the same defect of LLE and LE, the authors also refined LLE by neighbourhood preserving embedding (NPE).

As similar as facial features representation in face recognition, manifold learning can also be utilized to investigate the age and expression's semantic distribution structure [31, 34, 35]. Guo et al. [36] studied the manifold structure, and the experimental results show that faces in different ages have diverse manifold structures. As shown in Fig. 2a, the manifold distribution of people whose age between 0 and 45 is in uniform and that for older than 60 is miscellaneous. Tenenbaum et al. [31] applied ISOMAP on Frey [37] database, and the resulting manifold structures of neural, happy and negative expression are shown in Fig. 2b. It can be seen that facial expression images of different individuals constitute distinct expression manifolds. Due to the discontinuity caused by different people's appearance, various people's facial expression image generate distinct expression manifolds. Though subspace analysis method has been applied in manifold structure analysis on facial age and expression, the manifold analysis of facial ethnic features remains open. Due to its effectiveness at the structure representation, this paper attempts to analyze ethnic facial features based on manifold learning.

Subspace analysis method has been applied in manifold structure analysis on facial age and expression, but the analysis on facial ethnic features is remained open. In [36], the authors found that age manifold structure exists in facial images, see Fig. 2a. As illustrated in Fig. 2b, ISOMAP [38] is executed in Frey facial expression database [37]. Neutral and happy's positive and negative expressions can be clustered into one individual's manifold. Due to the discontinuity caused by different people's appearance, various people's facial expression images generate distinct expression manifolds.

Anthropological researchers have investigated the facial features of partial Chinese ethnic groups and then studied the beginning, evolution and fusion of every ethnic groups [10, 11]. With the development of photography and image analysis techniques, 2D and 3D shape analysis-based morphometric and anthropometry emerge in response to the needs of developments. The geometric features could be extracted accurately and efficiently based on automatic landmarks. Recently, Geometric morphometry based on facial images and three dimension models has gained increasing popularity in analyzing facial features [39].

In this paper, we construct a Chinese ethnic face database including three ethnic groups living in different areas. The



(a) age [36] (b) expression [37]

Fig. 2 The manifold structure of age and expression detail o the collecting process will be introduced in Sect. 3. For each facial image included in this dataset, 20 geometric features are extracted according to anthropologic definitions and then used to investigate the low-dimensional ethnical manifold structure. Geometric features involved in this research include face width (x_1), mandible width (x_2), physiognomical face height-1 (x_3), morphological face height (x_4), forehead height (x_5), physiognomical face height-2 (x_6), nose width (x_7), mouth width (x_8), binocular width (x_9), pupillary distance (x_{10}), nose height (x_{11}), intercanthal width (x_{12}), eyebrow perimeter (f_{13}), eye perimeter (f_{14}), nose perimeter (f_{15}), mouth perimeter (f_{16}), eyebrow area (f_{17}), eye area (f_{18}), nose area (f_{19}) and mouth area (f_{20}) (see Fig. 3).

The geometric features of n face images can be denoted as $\{x_1, x_2, \dots, x_n\}$, where $x_i \in R^D$ and D represents the number of features. We assume that $\{x_1, x_2, \dots, x_n\}$ is a d-dimensional manifold structure M embedded into space R^D, in which $d \ll D$. Then we can find a low-dimensional representation $\{y_1, y_2, \dots, y_n\}$ to replace the original data, where $y_i \in R^d$. As indicated in Fig. 4, Uyghur, Korean and Zhuang is respectively represented by green, blue and yellow colour respectively. All face images are divided into two groups with gender, Fig. 4a–d give the Laplacian and LPP manifold structures of three ethnic groups' male and female samples.

Figure 4 shows that the facial features obtained by anthropologic definitions are chaotically distributed in Laplacian and LPP manifold spaces, and the samples belong to different ethnic groups do not generate their sub-manifold structures with ethnic semantics. This is because that the anthropologic measurement indicators are mainly defined by the distance between facial components, and the resulting feature dimension is relatively low. The manifold structure generated by conventional anthropologic indicators fails to form smooth manifold structure distributed with ethnic semantics. Therefore, ethnic semantic manifolds can not be well represented with anthropologic indicators in Laplacian and LPP manifold spaces. We have investigated the facial semantic features of several Chinese ethnic groups with axiomatic fuzzy set theory, and the results show that the performance of ethnic groups recognition with anthropologic features is relatively poor [41]. In summary, this paper attempts to address the following problems.

Q1 Do the sub-manifold structures with ethnic semantics of Chinese ethnic groups exist?

O2 What kind of geometric features can represent Chinese ethnic facial attributes well?

3 Multi-ethnic face dataset

This paper focuses on the facial features manifold structure of Chinese ethnic groups. As shown in Table 1, three ethnic groups, which live in northeast, northwest and south China are used as the research ethnic subjects. The reason why these three groups are selected is that they distribute in isolated areas, which could guarantee the effectiveness of the facial features of individuals in each group. Hence, the individuals of Zhuang, Uyghur and Korea which live in Guangxi, Sinkiang and Gilin province respectively, are utilized to create a dataset for our research (see Fig. 5). For each ethnic group, 100 participants (50 males and 50 females) are recruited from Dalian Minzu University. The frontal face images are captured to construct the proposed dataset. Their ages are restricted between 21 and 23, in order to reduce the influence on facial ethnic analysis caused by age. During the collection of the proposed Chinese multi-ethnic face dataset,

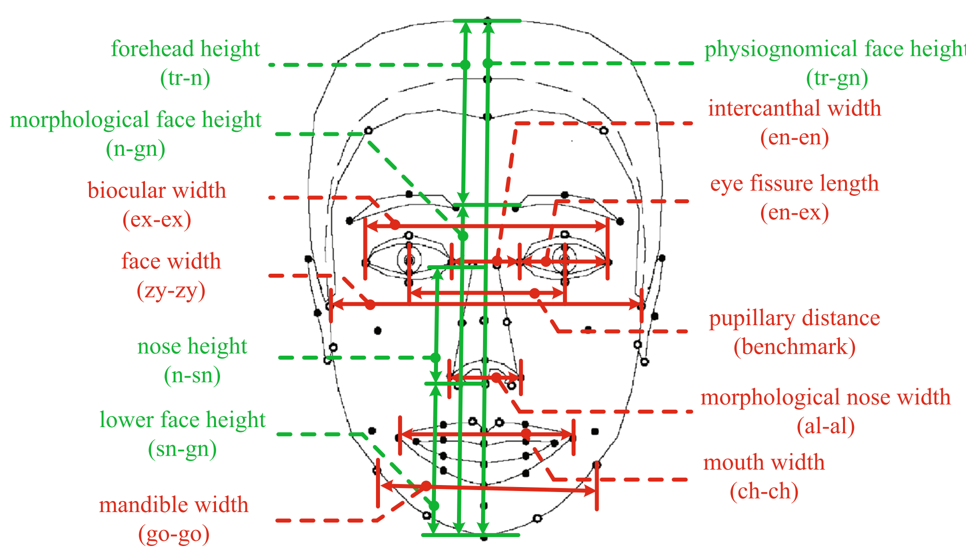
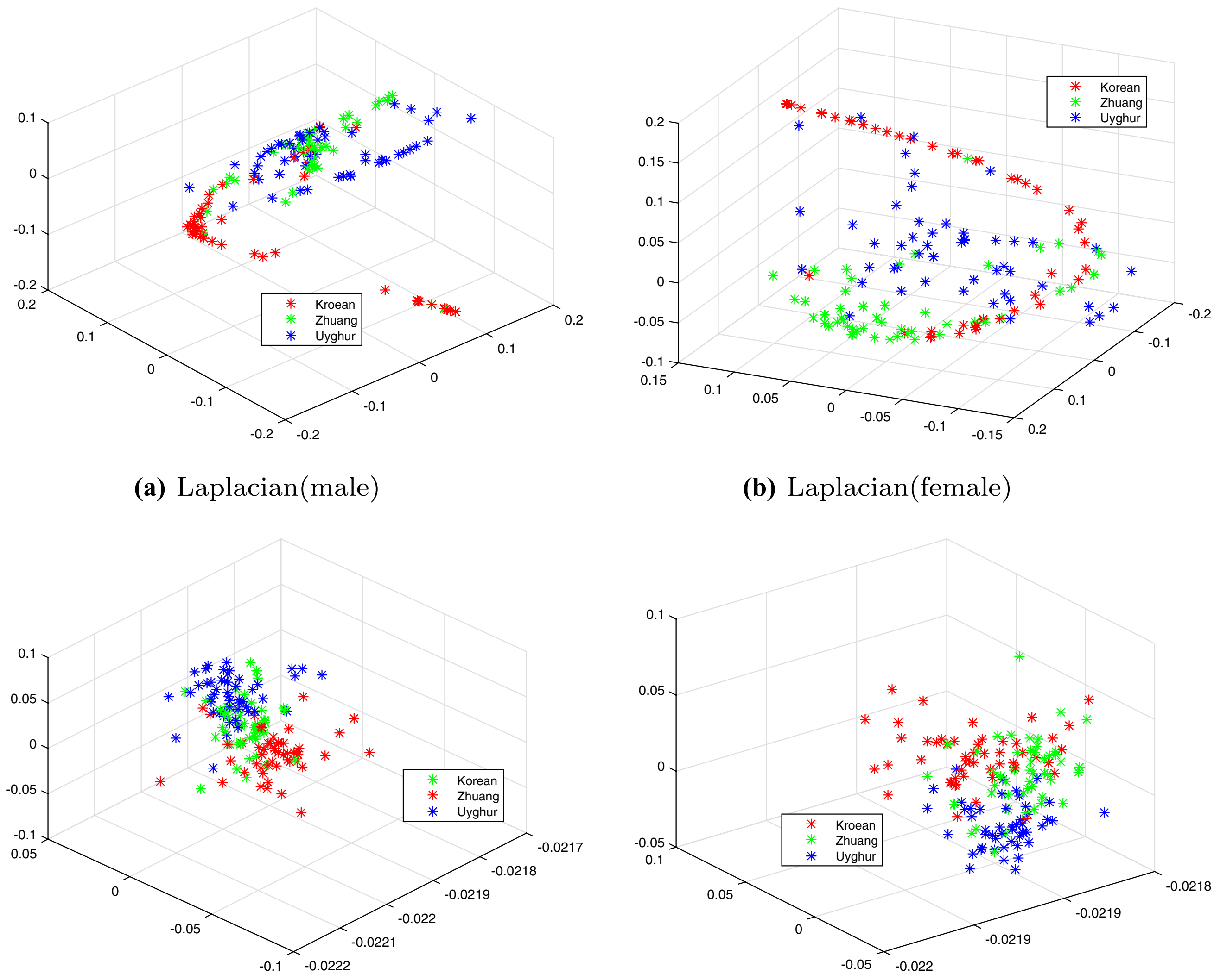


Fig. 3 The geometric features[40]



(a) Laplacian(male)

(b) Laplacian(female)

(c) LPP(male)

(d) LPP(female)

Fig. 4 The manifold structure of three ethnic groups

Table 1 The ethnic groups with more than millions of people in China

Ethnic group	Population	Proportion (%)	Location
Zhuang	16,926,381	1.27	Guangxi
Uyghur	10,069,346	0.76	Xinjiang
Korean	1,830,929	0.14	Jilin

a digital photography studio (see Fig. 6) and acquisition scale are set up as standard capturing environment. Figure 7 gives the samples of captured facial images. The dataset can be download from http://zs.dlnu.edu.cn/minzu300face.rar.

4 Facial landmark extraction and similarity calculation

In anthropology, obtaining facial geometric features mainly depends on craniofacial measuring. Other indicators like skin color or texture are liable to be affected by varying environment. Actually, anthropometry is different with image-based facial ethnic feature extraction. The former is built based on accurate craniofacial measuring and the latter is defined with distance between pixels rather than actually measured geometric features. Hence, the pixels-based distances should be normalized. A statistical analysis is conducted with the measured distance-based features, and the variance of eye width is relatively small. Therefore, the average eye separation between left eye center and right eye center serves as the 'unit' distance for distance indicators

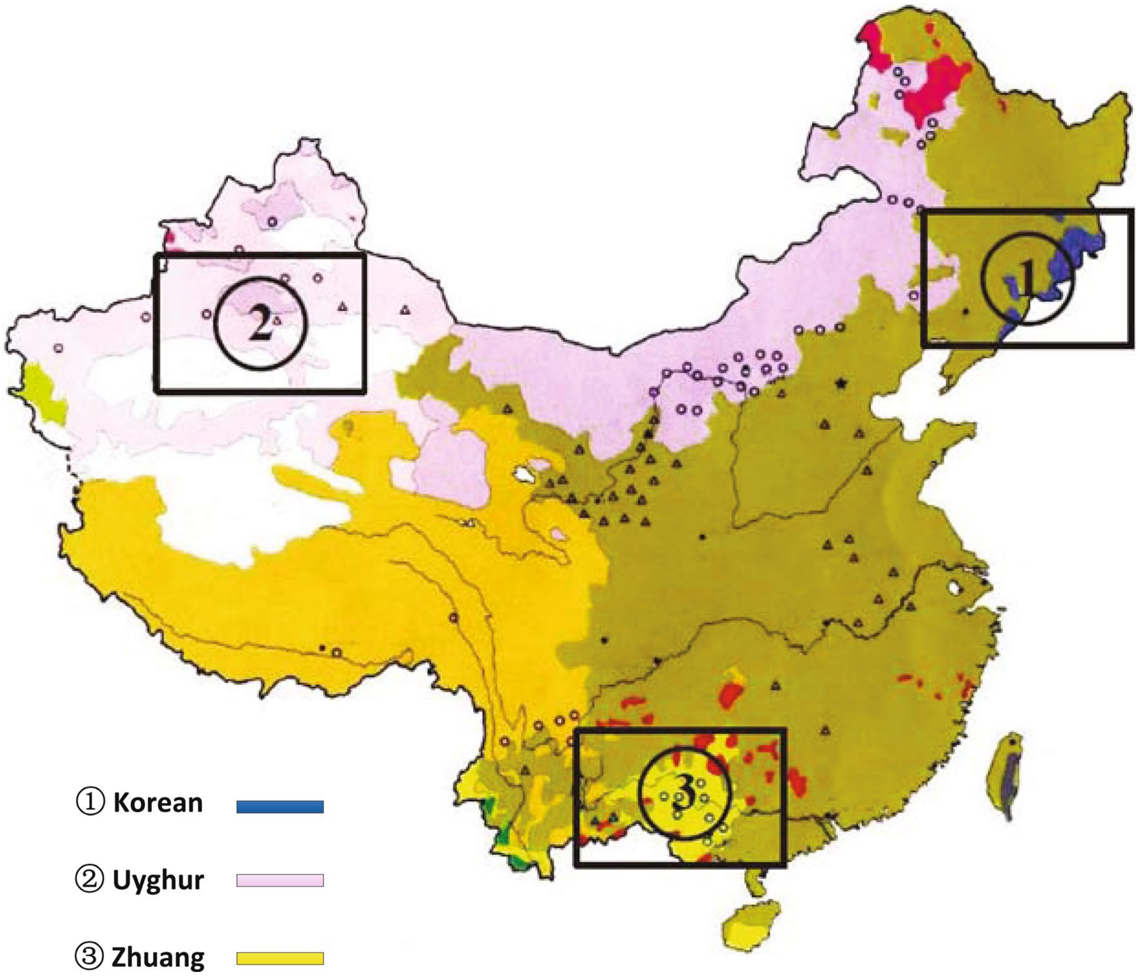


Fig. 5 The geographic distribution of selected ethnic groups in China [40]

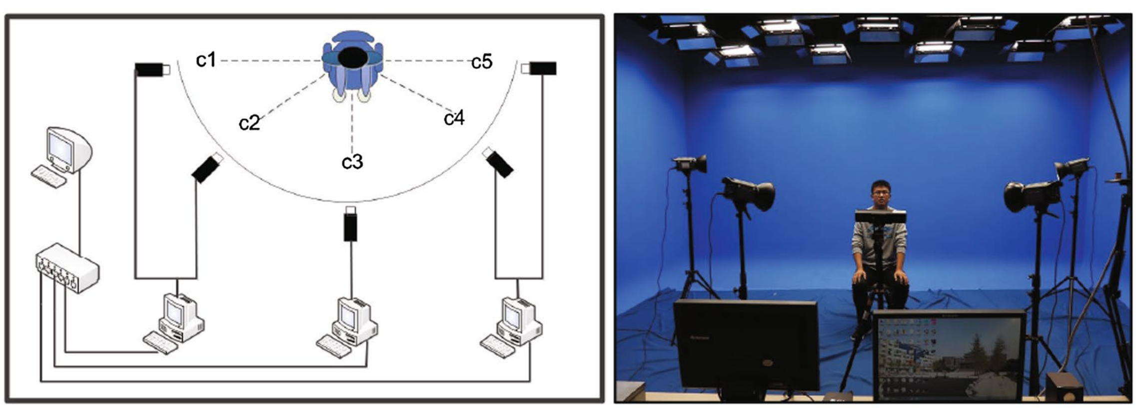


Fig. 6 The digital photography studio and scale for capturing facial image

normalization. Meanwhile, the angle and index given below are immune to the variation of face image, which implies that they are more stable than other indicators. All above mentioned indicators including distance, angle and index intensively depend on face landmark location algorithm, which means an accurate and efficient facial landmark detector is required. This paper adopts STASM [42], is introduced to extract facial landmarks. Since the number of obtained

Fig. 7 The samples of captured facial image

landmarks by STASM is relatively small, the scale of geometric features could be under control. Figure 8 shows the 77 landmarks obtained by STASM.

5 Facial high-dimensional geometric feature selection

Digitalized human face belongs to an extremely high-dimensional geometric features space. For example, a picture with 480×640 pixels includes 307,200 features, and we can generate 2926 distances, about 210,000 angles and about 4,100,000 indexes based on the detected landmarks. The dimension of geometric features are significantly larger than pixels. Let landmark set be $F = [l_1, l_2, \dots, l_N]^T (N = 77)$, then distance, angle and index can be denoted as $d(l_i, l_j) = ||l_i - l_j||_2$, $\beta_i = \arccos \frac{d(l_i,l_j)^2 + d(l_i,l_q)^2 - d(l_j,l_q)^2}{2 \times d(l_i,l_j) \times d(l_i,l_q)}$ and $r = \frac{d(l_i,l_j)}{d(l_a,l_b)}$ respectively, where $\forall l_i, l_j, l_a, l_b \in \{l_1, \dots, l_N\}$. Because of the symmetry of face structure, the obtained features are usually redundant. LE and LLE is carried out on the data set that consists of 2926 distance features, and the result is shown in Fig. 9a. Obviously, the distribution of samples belonging to different ethnic groups is chaotic rather than independent. Therefore, filtering redundant features is necessary.

Considering the relevance and redundancy between features, we adopt space searching-based minimal redundancy maximal relevance (mRMR) [43, 44] technique to select geometric features. Mutual information is utilized to evaluate the relevance and redundancy between features, and information difference and information entropy serve as cost function to search optimal subset of features. The main idea of mRMR is finding salient features based on maximal statistical dependent principle.

Maximal relevance and minimal redundancy in mRMR are defined as Eqs. (1) and (2),

$$\max D(F, c), D = \frac{1}{|F|} \sum_{x_i \in S} I(f_r, c), \tag{1}$$

$$\min R(F), R = \frac{1}{|F|^2} \sum_{f_r, f_o \in F} I(f_r, f_o), \tag{2}$$

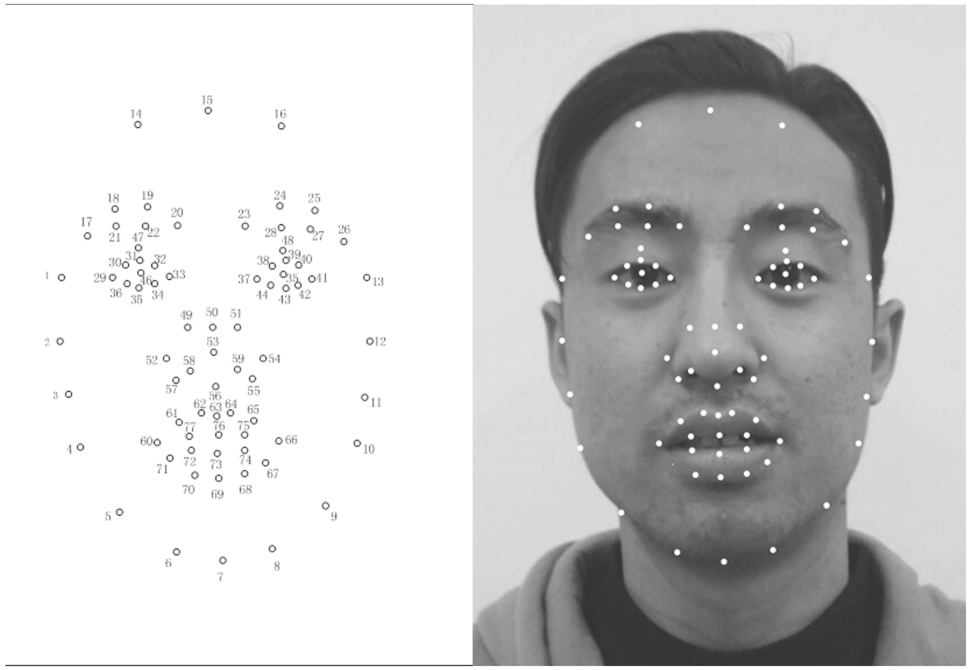
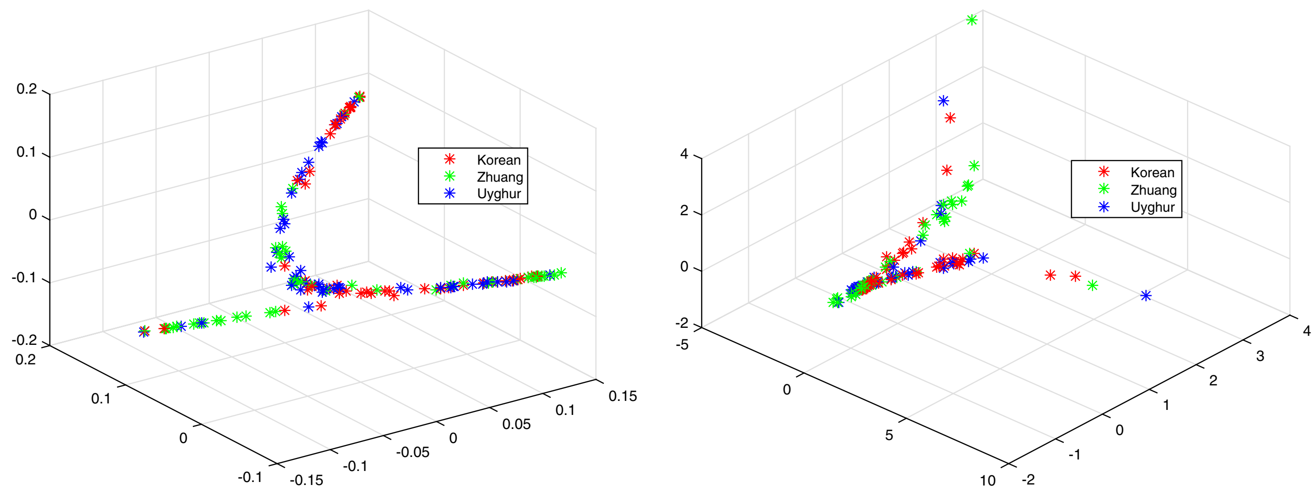


Fig. 8 The landmarks and their location obtained by STASM



(a) Laplacian **(b)** LLE

Fig. 9 The manifold structure of male datasets with 2926 distance features

where F is the set of facial features, c is the set of class labels, $I(f_r, c)$ represents the mutual information between f_r and class c and $I(f_r, f_o)$ denotes the mutual information between f_r and f_o. Given two random variables x and y, let their probability density be $p(x)$, $p(y)$ and $p(x, y)$, their mutual information can be defined by Eq. (3).

$$I(x;y) = \iint p(x,y) \log \frac{p(x,y)}{p(x)p(y)} dxdy, \tag{3}$$

Equation (4) serves as the evaluation function for feature selection.

$$\begin{cases} \max \Phi_1(D,R), \Phi_1 = D - R \\ \max \Phi_2(D,R), \Phi_2 = \frac{D}{R} \end{cases}. \tag{4}$$

Given the fact that the dimension of facial geometric features are extremely high, traditional database may be only adaptive for dataset with low dimension feature. Therefore, we use MongoDB [45] to store angle and index with high dimension. In practical implementation, we divide 219,450

Table 2 The selected geometric features

Dimension	Distance	Angle	Index
Original feature	2926	219,450	4,279,275
Selected feature	195	250	500

angles into 22 subsets in order to improve the efficiency of mRMR. Similarly, 4,279,275 indexes are divided into 455 datasets.

According to the weight of features obtained by mRMR, we firstly select optimal features from divided datasets and combine them into a new dataset, then pick up salient features from the combined dataset. Finally, we select 195 distances, 250 angles and 500 indexes for ethnic feature representation (see Table 2). The selected features are then utilized to conduct manifold analysis. The sample spaces of three ethnic groups are visualized to verify whether sub-manifold structure of different ethnic groups' face exist under the proposed indicator system. Moreover, we also evaluate the effectiveness of filtered features for ethnic classification using several classifiers in Weka.

6 The facial manifold analysis with different geometric features

This paper conducts manifold analysis on five datasets consisting of distance, angle or index, with the purpose of investigating the sample space manifold structures of ethnic groups based on different features.

6.1 Multi-ethnic facial manifold analysis based on distance features

Distance is one of the most commonly used geometric feature by anthropologic researchers. In this paper, 2926 distance-based features are generated based on 77 landmarks. The experiment results in Sect. 2 show that the sub-manifold structures of different ethnic groups are not clearly separated in low-dimensional space based on anthropologic distances, which may be caused by feature redundancy. Therefore, we utilize mRMR to filter 195 distance-based features to construct new dataset. The 195 distances-based features are ordered according to the weight obtained by mRMR. For all distances, we divide them into five parts: [0.15, 0.452), [0.05, 0.10), [0.01, 0.05) and (0.0, 0.05). Table 3 gives the comparative analysis between features of top 4 and anthropology ones, where the bold features are included in selected 195 distances.

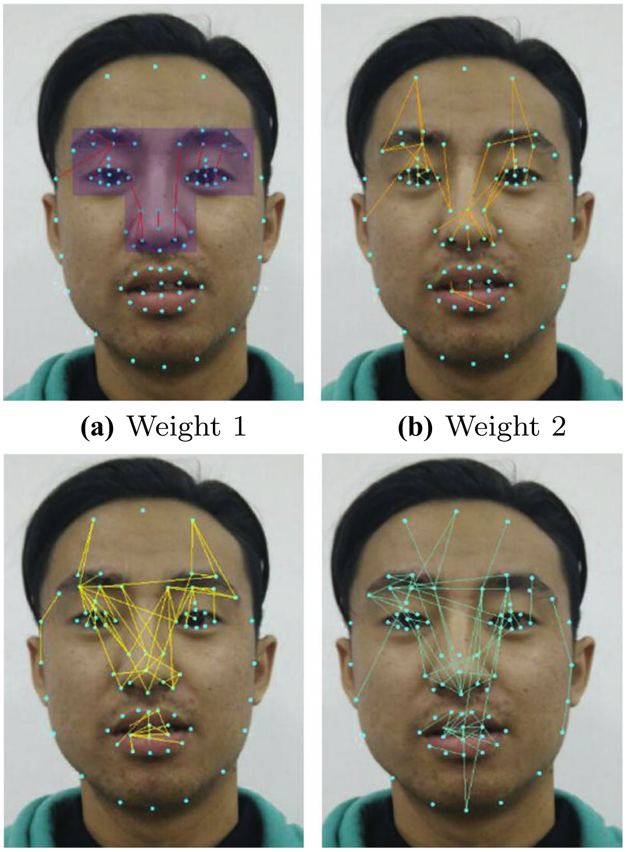
In order to analyze the semantic characteristics of filtered features intuitively, the distribution of these features is visualized on face image. As indicated in Fig. 10, red, orange, yellow and green represent features belong to weight 1(19), weight 2(37), weight 3(63) and weight 4(65), respectively. The 'T' area which is consisted of eyebrow, eye and nose has strong relationship with ethnic features semantics. Despite the 'T' area, it is also can be seen that the semantic feature description also includes the mouth area.

Table 3 The distance features belong to first four parts filtered by mRMR

Weight	Characteristic of weight area
1	Eye fissure length
	Distance between eyebrow and eye
	Distance between eyebrow and nose
	Nose length
2	Eyebrow length
	Forehead width
	Distance between nose and eye inner corner
	Lower lip thickness
3	More subtle nose and mouth features
4	Distance between eyebrow point and mouth
	Distance between mouth and jaw
	Distance between eyebrow and ear
Anthropology	Morphological face height
	Morphological face width
	Nose width
	Nose height
	Lip thickness
	Mouth fissure length
	Inner eye corner width
	Outer eyepoint distance
	Inner eyepoint distance
	Zygomaticus width
	Jaw length
	Distance between jaw corner

Table 3 and Fig. 10 indicate the following information.

- The features with high weight in filtered feature set are slightly different from anthropometric definitions. Only four anthropometric features are included in the feature set obtained by mRMR.
- Facial features which are related to ethnic groups mainly locate in eye, eyebrow and nosewing region. Specifically, the distances among eyebrow, eye and nose can also reflect the difference between ethnic groups.
- The correlation between face shape and ethnic features is quite insignificant. It can be seen that the landmarks of face contour are excluded in selected feature set except for ear-related ones.
- Nose has a strong descriptive capability for ethnic features, but these feature are ignored in anthropometric research.



(a) Weight 1 **(b)** Weight 2

(c) Weight 3 **(d)** Weight 4

Fig. 10 The weight region of distance feature

- Mouse area is highly related to ethnic features. The relations are mainly reflected by the width and height of upper lip and lower lip, which are consistent with anthropometric indicators.

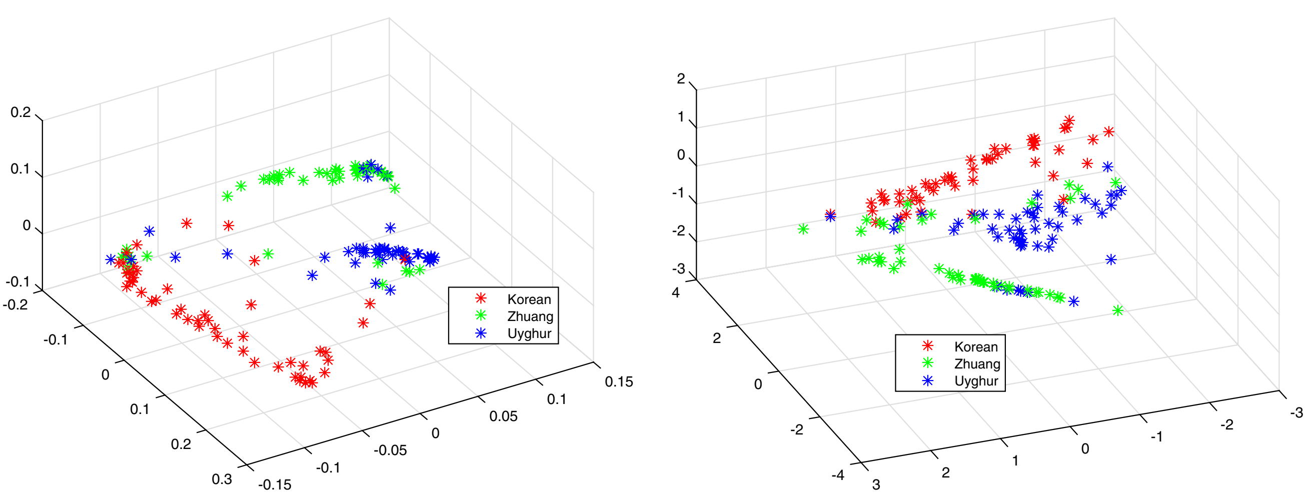
We have selected 195 distance features from 2926 ones using mRMR feature selection method. The selected features are utilized to construct a dataset, based on which ethnic manifold learning is conducted. As shown in Fig. 11, we utilize Laplacian and LLE to learn the ethnic manifold distribution. The red, green and blue markers represent the samples of Korean, Zhuang and Uyghur respectively. The results show that every class of data can generate the sub-manifold structures related to its ethnic semantics, using the selected distance-based feature representation.

The sub-manifold structures obtained by Laplacian and LLE show that the samples of three ethnic groups can generate independent manifold distribution with the filtered features, which also validates the effectiveness of selected distance features. These features can preserve the difference between ethnic groups in some extent.

6.2 Multi-ethnic facial manifold analysis with angle features

Landmarks near eye corner are commonly used to describe face. Since inner eye corner and outer eye corner can represent eye shape, and the angle between tragion and mandible can depict the index of face length. The angles formed by facial landmarks can describe not only the shape of individual facial component, but also can represent the distribution relation between pairs of facial components.

Based on 77 landmarks, 219,450 angular features can be generated by triangulation. Similar to the process of distance-based features, the angular features are selected by



(a) Laplacian **(b)** LLE

Fig. 11 The manifold structure of distance features mRMR, and then the filtered features are utilized to conduct manifold analysis. Table 4 lists the relationship between facial landmarks and the filtered angular features. In order to characterize the angle features with different weight, the selected 250 angle features are shown in Fig. 12. According to the weight, the filtered features are categorized into four regions, and the coloured triangular means that the angular features of this area have higher weight.

Figure 12 and Table 4 show that angles with high weight mainly locate in the region which is consisted of eyebrow, eye and nose. Moreover, eye fissure angle and nosewing angle are the most significant region. This computational selected area is consistent with the salient region used by anthropometric definitions.

In order to conduct manifold analysis based on angular features, PCA and LDA are applied to learn the manifold structure of three ethnic groups. As shown in Fig. 13, the first three principal components of ethnic samples are illustrated. It can be seen that the distributions of three ethnic groups' facial samples are clearly separable under the filtered ethnic semantic description.

6.3 Multi-ethnic facial manifold analysis with index features

Index is defined as the percentage of absolute value between two measurement indicators. Compared with directly measurement value, index reflects a proportional relation of facial shape. Index is capable of eliminating noise caused by individual's difference. Therefore, index is widely applied in anthropology. For different ethnic groups, their facial index features can also be utilized to describe ethnic ethnic semantics. Table 5 gives the anthropometric definitions of index, including 15 features of frontal face and 3 features of side face.

We firstly use these index features defined by anthropometric researchers to evaluate their effectiveness in ethnic feature representation. The Laplacian and ISOMAP are applied to conduct manifold analysis, and the results are shown in Fig. 14. It can be seen that the some datasets with features obtained by anthropometric definitions

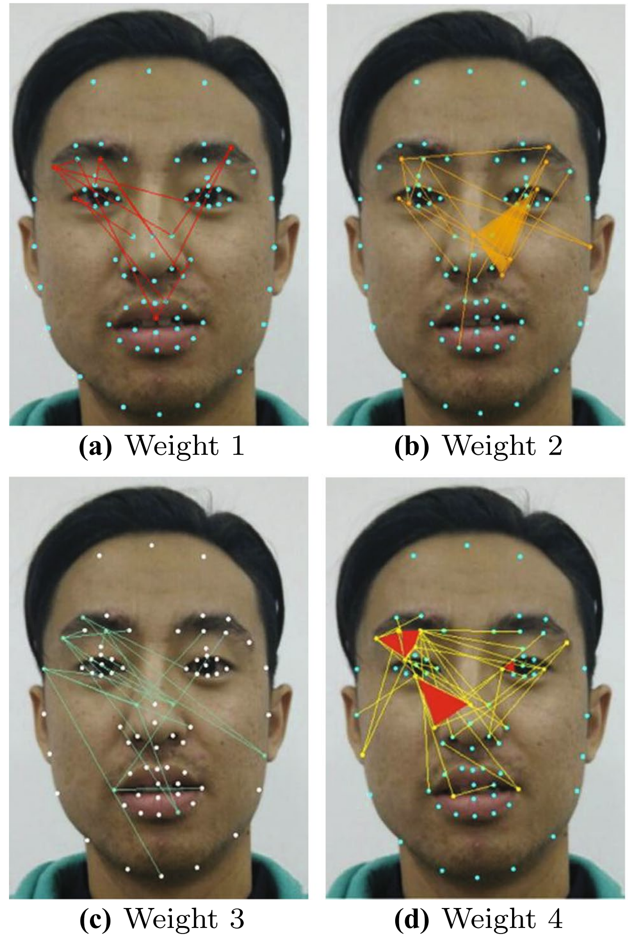


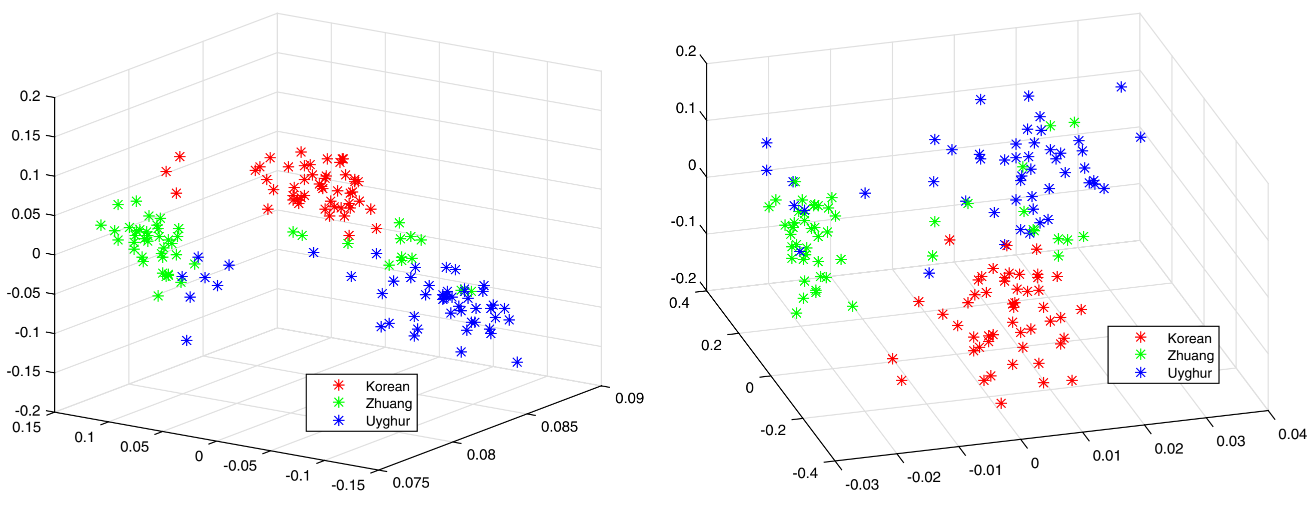
Fig. 12 The weight region of angle feature

can generate clear sub-manifold structures with Laplacian, such as Korean (female) and Zhuang (female). But the sub-manifold structures of Korean (male) and Zhuang (male) are in chaos. Meanwhile, the manifold structures obtained by ISOMAP show that male and female generate corresponding clusters. However, Korean is mixed with Uyghur, and clear boundary does not exist in these two ethnic groups' samples.

In this section, we also utilize mRMR to select the proposed index features that can characterize ethnic facial

Table 4 The angle features belong to first four parts filtered by mRMR

Weight	Corner point	Characteristic of weight area
1	Eyebrow point	Angles built by eyebrow, inner eye point and nasion
	Nasion	Generate the relation hotspot
2	Eyebrow point	Between nosewing and nose eye
	Tragion	Angle
3	Eyebrow	Eye fissure angle, angle relation
	Eye corner point	Between eyebrow and eye, nosewing angle relation
4	Eyebrow	More accuracy location relation
	Mouth	Among eye, nose and mouth



(a) PCA **(b)** LDA

Fig. 13 The manifold structure of angle features

Table 5 The 15 anthropometric index in frontal face

Number	Name
1	Length-breadth index of head
2	Transverse frontoparietal index
3	Transverse cephalo-facial index
4	Morphological facial index
5	Morphological upper facial index
6	Physiognomic facial index
7	Zygomatic mandibular index
8	Zygomatic frontal index
9	Physiognomic upper facial index
10	Fronto-facial index
11	Physiognomic upper facial height index
12	Vertical cephalo-facial index
13	Nasal index
14	Breadth-depth index of nose
15	Lip index

characteristics. Due to the high dimension of raw data, we divide the dataset into 455 parts according to the dimension of features. For each partition, we select 7124 features from that if the score of the features is larger than 0.23. The selected features from different parts are then integrated into a new dataset, and 500 index features are picked out form 4,279,275 ones using mRMR feature selection.

As shown in Fig. 15, we depict four class index features with high weight. The distances with the same colour construct an index feature. Eye fissure width, distance between eyebrow and eye, nosewing length, distance between nosewing and inner eye corner and distance between nosewing and eyebrow appear in all features with different weights. Moreover, the distances between mouth and forehead width or eye have high appearance frequency. The selection results show that these features are important for distinguishing these three ethnic groups. Table 6 gives the description of 15 index features with high weight.

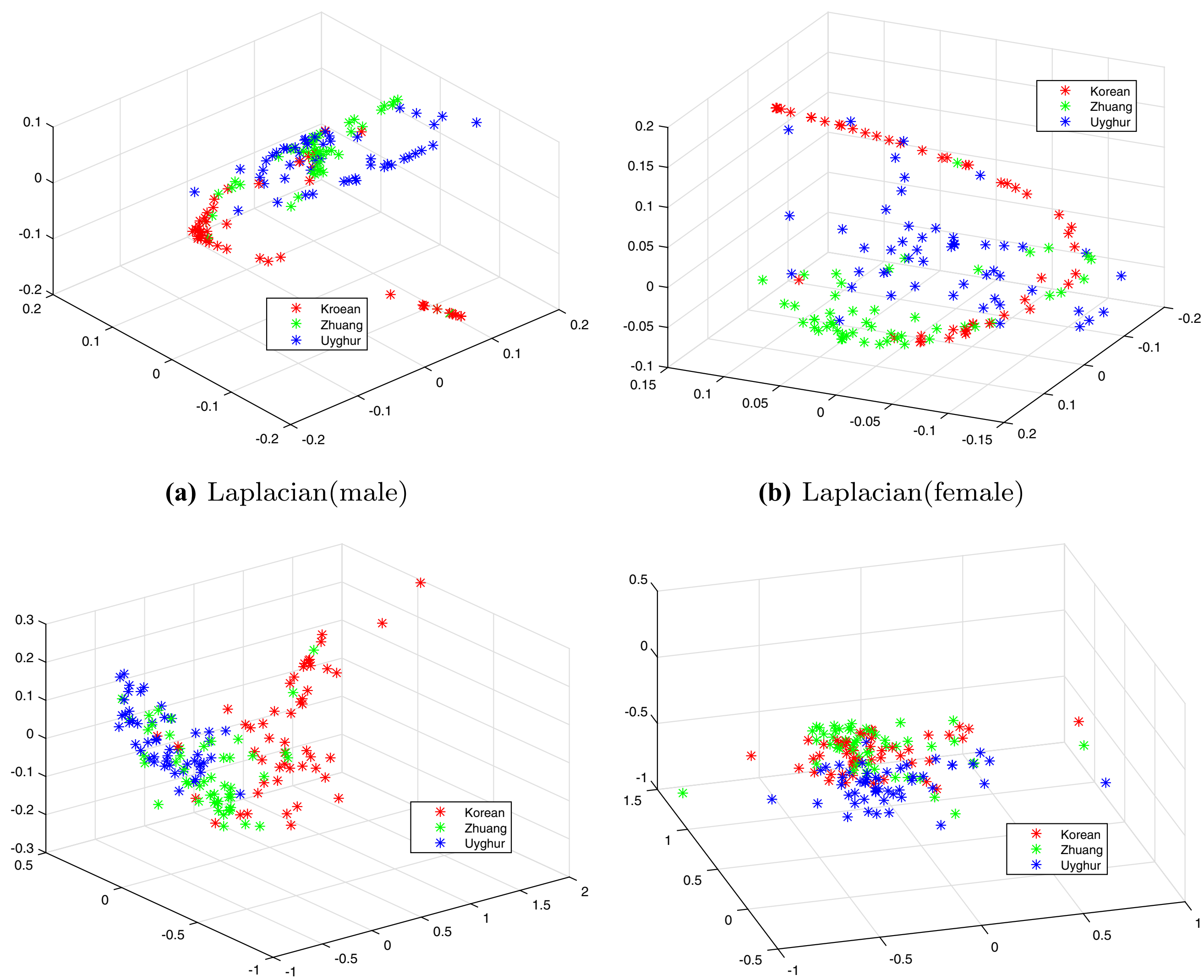
The manifold analysis is also conducted on the dataset with these filtered 500 features. PCA, LDA, LLE and LPP are utilized to implement dimensional reduction. As shown in Fig. 16, the distribution of three ethnic groups' data is clearly separated, and every class can generate independent cluster. For Laplacian and LPP, the visualized manifold distributions show that they are relevant with corresponding ethnic semantics.

6.4 Multi-ethnic facial manifold analysis with mixed features

In above sections, we have investigated three types of geometric features individually, including distance, angle and index. These features can generate the semantic description of ethnic facial features. However, which type of feature in more powerful in ethnic representation is still unclear. In order to study this issue, these features are mixed together to conduct manifold analysis.

The mixed feature dataset is consisted of 250 distance-based, 500 angular and 500 index features. The mRMR is applied to select 51 features whose score ≥ 0. The obtained percentage of distance-based, angular and index features are 0, 14.6 and 85.4%. Table 7 gives the details of these features including category, computation method and weight.

Table 7 shows that distance-based feature is poor in describing the difference of ethnic facial features, which is consistent with human cognition. For example, people



(a) Laplacian(male) **(b)** Laplacian(female)

(c) ISOMAP(male) **(d)** ISOMAP(female)

Fig. 14 The manifold structure of index features computed by anthropometric definition

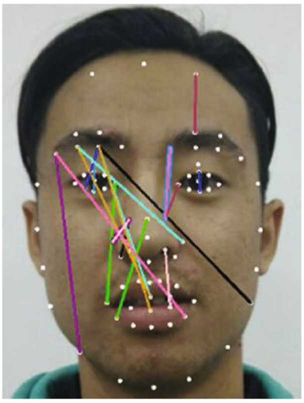
can recognize the ethnicity of young and adult, although the distance features of their face exist large difference. Furthermore, the number of index features is significantly larger than that of angular features in filtered feature set. In this section, frequent pattern mining is used to analyze the features listed in Table 7. Tables 8 and 9 give the support degree of edge and vertex that are used to generate index and angle.

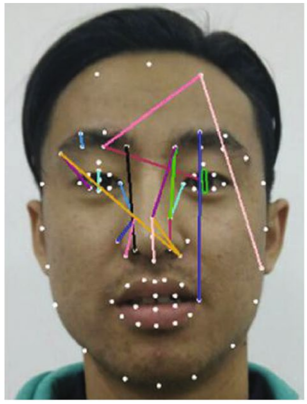
As shown in Table 7, the most frequent information is related with eye fissure and nosewing. The statistical result is indicated in Fig. 17. The percentage of landmarks, which locate in the region composed of nose, eye and mouth is more than 85%. It implies that nose and eye region reflect more ethnic facial features than other facial components.

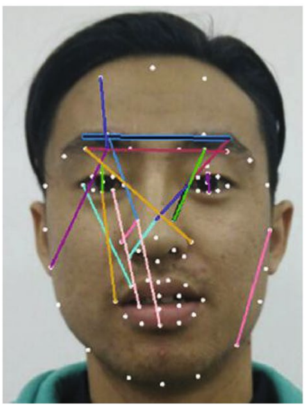
The manifold structure of dataset is also learned based on the filtered mixed features by PCA. As shown in Fig. 18, the result is similar with that of dataset with index feature, but the distribution of mixed features is more clear. The above experiments show that index is the most important indicator in characterizing ethnic facial semantics. Moreover, the index and angular features can describe ethnic faces more precisely.

7 Validation analysis

In order to evaluate the effectiveness of different facial geometric features, 5 datasets with different features are constructed based on the collect images. First, image pre-processing,


(a) Weight 1


(b) Weight 2


(c) Weight 3

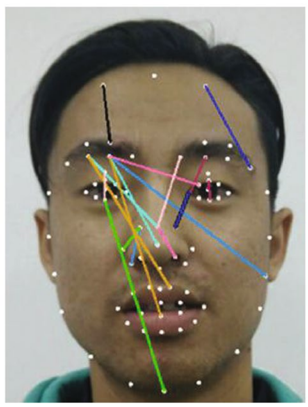

(d) Weight 4

Fig. 15 The weight region of index feature

landmark extraction, geometric feature extraction are carried out on the acquired facial image dataset including Uyghur, Zhuang and Korean. Then, we build 5 datasets including dataset A with conventional 22 distances, dataset B with 195 distances, dataset C with 250 angles, dataset D with 250 indexes and dataset E with 51 mixed features to conduct ethical group classification. Several classifiers are used to perform ethnic classification on these five datasets to verify the effectiveness of the proposed features. All experiments are implemented on the following conditions.

- Hardware environment: Intel(R) Core(TM) i7-4770 CPU, 8 G Memory;
- Software environment: Operation System Window 7;
- Classifiers: Weka version 3.6 [46].

In order to compare the results achieved by different classifiers, we introduce several evaluation metrics including TP Rate, FP Rate, Precision, Recall, F-Measure and AUC as defined below. For the multi-class classification problem, let $Y = \{y_1, y_2, \dots, y_k\}$ be the class labels of samples. Firstly, the multi-class classification problem is viewed as a k binary class classification issue. For each class $y_i \in Y$, a binary classifier is built, where all samples belong to y_i are viewed as positive samples and other samples are viewed as negative samples. TP Rate, FP Rate, Recall, Precision, F-Measure and Accuracy can be computed by the following equations:

$$TR\ Rate = \frac{TP}{TP + FN}, \tag{5}$$

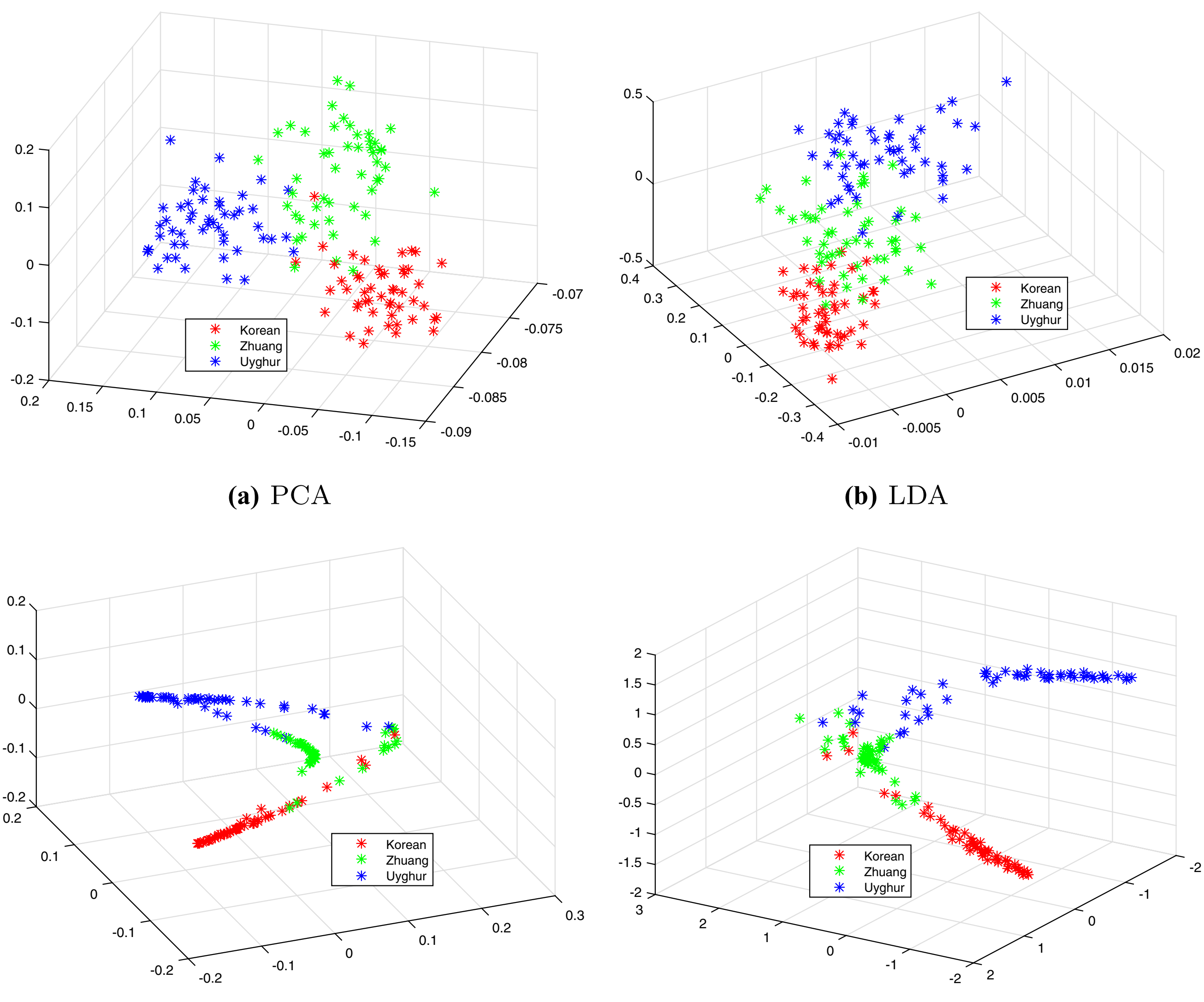
$$FP\ Rate = \frac{FP}{FP + TN}, \tag{6}$$

$$Recall = \frac{TP}{TP + FP}, \tag{7}$$

$$Precision = \frac{TP}{TP + FP}, \tag{8}$$

Table 6 The index features with different weight

Number	Characteristic of weight area	Weight
1	Eye fissure height/distance between eyebrow and eye	0.329
	Eye fissure height/distance between nosewing and eyebrow	0.362
	Distance between nosewing and eyebrow/distance between mouth and eyebrow point	0.312
	Distance between nosewing and inner eye corner point/forehead height	0.35
2	Eye fissure height/distance between nosewing and eyebrow	0.302
	Nosewing length/distance between eyebrow and eye	0.302
	Distance between eyebrow and eye/distance between eyebrow and nosewing	0.301
	Nosewing length/distance between eyebrow and mouth	0.302
3	Eye fissure height/distance between nosewing and eyebrow	0.3
	Distance between nosewing and inner eye corner point/forehead height	0.294
	Nosewing width/distance between mouth and outer eye corner point	0.297
	Eye interval distance/distance between nosewing and inner eye corner point	0.297
4	Eye fissure height/distance between nosewing and inner eye corner point	0.274
	Distance between eyebrow and upper lip/distance between eyebrow and lower lip	0.283
	Nosewing length/distance between eye and underjaw	0.281



(a) PCA **(b)** LDA

(c) Laplacian **(d)** LLE

Fig. 16 The manifold distribution of the dataset with index features in low dimensional space

$$F\text{-}Measure = \frac{2 \times Precision \times Recall}{Precision + Recall}, \tag{9}$$

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN}, \tag{10}$$

where TP, FN, FP and TN represent the number of positive samples correctly predicted as positive class, the number of positive samples wrongly predicted as negative class, the number of negative samples wrongly predicted as positive class and the number of negative samples correctly predicted as positive class.

In each experiment, we divide every dataset into two parts according to gender. Therefore, the above mentioned five datasets can generate ten new datasets, and then ten-fold cross-validation is utilized to evaluate the performance in every case.

Table 10 gives the result of decision tree on all datasets. The pruning threshold is set to 0.25. The results show that the performance on the dataset with mixed features is the best among all cases. No matter for male or female, the classification performances on all datasets with angular features are superior to that with index or distance feature.

Naive Bayes with K2 searching algorithm and 'SimpleEstimator' is utilized to evaluate the capability for every feature. As shown in Table 11, the result shows that Naive Bayes approach achieves the best performance on male or female datasets with mixed features. For the male datasets, index features outperform other features. For the female features, angle features is superior to index features.

Table 7 The mixed features with different weight

Number	Category	Equation	Weight	Number	Category	Equation	Weight
1	I	(49,57)/(22,7)	0.669	27	I	(39,43)/(7,22)	0.299
2	I	(35,47)/(23,51)	0.362	28	I	(49,69)/(34,72)	0.296
3	I	(37,51)/(16,24)	0.35	29	I	(22,73)/(21,64)	0.298
4	I	(39,43)/(22,36)	0.329	30	I	(49,52)/(15,7)	0.296
5	I	(50,71)/(33,60)	0.33	31	I	(35,47)/(28,51)	0.298
6	I	(49,52)/(5,17)	0.312	32	I	(25,50)/(21,27)	0.292
7	I	(22,76)/(21,54)	0.312	33	I	(37,51)/(14,19)	0.294
8	I	(51,59)/(22,45)	0.302	34	A	$\angle$(21,55,26)	0.289
9	I	(31,35)/(37,51)	0.305	35	I	(39,43)/(28,51)	0.287
10	A	$\angle$(51, 59, 27)	0.311	36	I	(49,52)/(22,38)	0.289
11	I	(39,43)/(20,58)	0.302	37	I	(49,76)/(35,72)	0.289
12	I	(37,59)/(14,22)	0.302	38	I	(50,52)/(22,60)	0.286
13	I	(17,36)/(23,50)	0.302	39	I	(35,47)/(23,50)	0.287
14	I	$\angle$(31, 22, 33)	0.297	40	I	(49,52)/(7,35)	0.287
15	I	(49,52)/(60,74)	0.304	41	I	(22,53)/(21,50)	0.284
16	I	(50,55)/(17,55)	0.301	42	I	(50,70)/(33,60)	0.285
17	I	(18,21)/(33,49)	0.302	43	A	$\angle$(17,49,21)	0.285
18	I	(35,60)/(21,54)	0.305	44	I	(37,51)/(16,24)	0.285
19	I	(39,43)/(23,51)	0.303	45	I	(37,51)/(16,24)	0.282
20	I	(37,51)/(18,25)	0.301	46	A	$\angle$(51,25,59)	0.283
21	I	(22,73)/(21,76)	0.300	47	A	$\angle$(33,29,49)	0.284
22	I	(49,52)/(24,66)	0.303	48	I	(49,57)/(22,43)	0.282
23	I	(49,57)/(14,22)	0.302	49	I	(39,43)/(19,49)	0.282
24	I	(50,57)/(29,61)	0.296	50	A	$\angle$(21,49,25)	0.281
25	A	$\angle$(21,36,22)	0.299	51	I	(31,35)/(24,51)	0.279
26	A	$\angle$(22,60,50)	0.298				

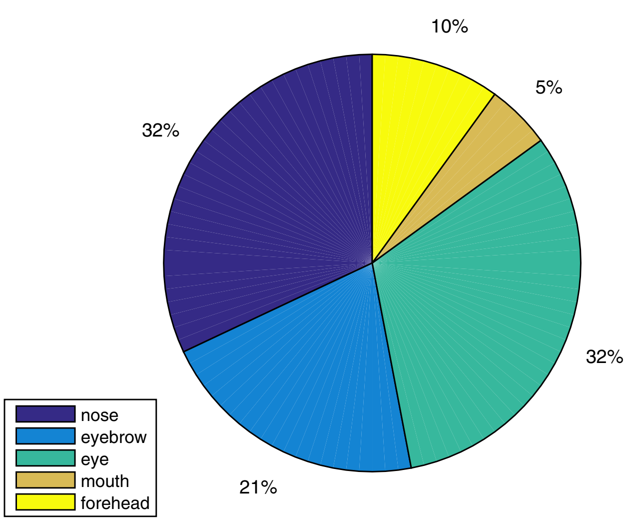


Fig. 17 The percentage of landmarks located in facial components

Table 8 The frequent items of edge in mixed features

ID	Edge	Supp	Name
1	39–43	6	Eye fissure
2	49–52	6	Nosewing length
3	37–51	4	Distance between nose and eye
4	35–47	3	Eye fissure
5	49–57	3	Nosewing width
6	22–73	2	Distance between eyebrow and mouth
7	31–35	2	Eye fissure
8	14–22	2	Forehead 1
9	16–24	2	Forehead 2
10	21–54	2	Distance between eyebrow and nose 1
11	23–50	2	Forehead between eyebrow and nose 2
12	23–51	2	Forehead between eyebrow and nose 3

Table 12 shows the results of BayesNet on all datasets. The classification performance on the dataset with mixed feature is the best both for male or female. For the male datasets, index features are commensurate with angular features. For the female datasets, the evaluation metric on index features is higher than that of angular features.

The results for the RBFNetwork are shown in Table 13, where the number of random seeds and the minimum standard deviation are set to 1 and 0.1, respectively. The datasets with the mixed feature achieve the best

Table 9 The frequent items of vertex in mixed features

ID	Edge	Supp	Name
1	22	16	Eyebrow
2	49	16	Nose
3	51	14	Nose
4	21	11	Eyebrow
5	50	10	Nose
6	35	9	Eye
7	37	7	Eye
8	43	7	Eye
9	52	7	Nose
10	39	6	Eye
11	24	5	Eyebrow
12	57	4	Nose
13	23	4	Eyebrow
14	31	3	Eye
15	46	3	Eye
16	14	3	Forehead
17	16	3	Forehead
18	73	2	Mouth
19	54	2	Nose

performance either for male or female. For the male datasets, index features are better than other features. For the female datasets, angular features are better than index features on all evaluation indicators except for AUC.

We utilize the C-SVC (a variation of SVM) whose kernel function is $e^{-r|u-v|^2}$ with $degree = 3$, $coef_0 = 0$ and $CacheSize = 40MB$ to implement the classification tasks on all datasets. The results are shown in Table 14. For the male datasets, the results on the dataset with mixed feature is equivalent with that with index feature. For male datasets, mixed feature outperforms than index feature.

Table 15 gives the classification result of SMO whose kernel is a polynomial function. For the male datasets, the performance on the datasets with mixed feature is close to that with index feature. For the female datasets, mixed feature is slightly superior to index feature.

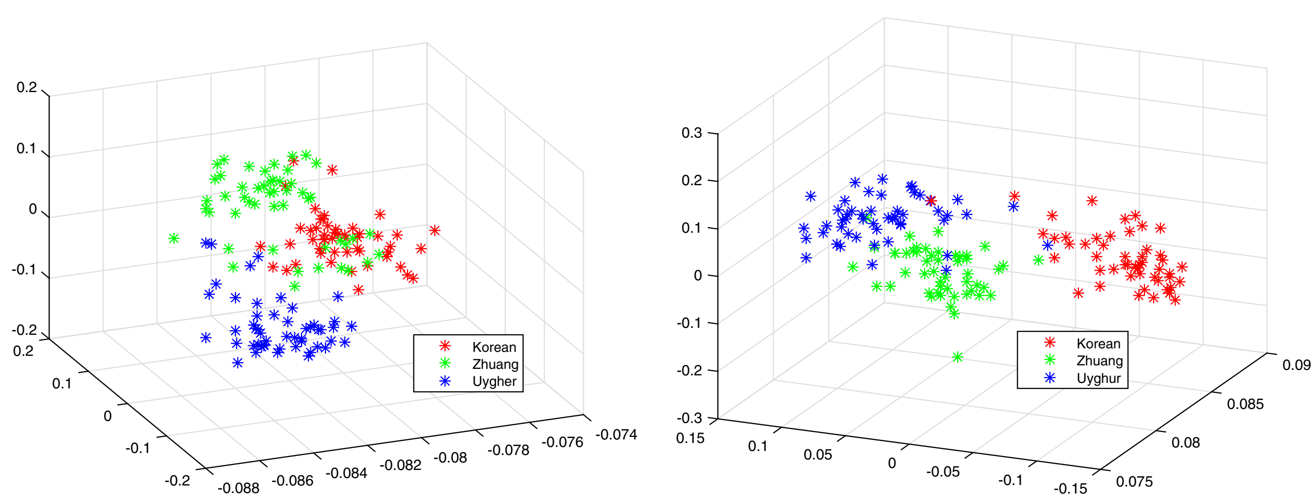
In order to determine the number of features based on different datasets, we order the features by the weight obtained by mRMR. Figure 19 gives the curve that describes the relation between the performance of algorithm and the number of features.

As shown in Fig. 19, we can find that the curve of the datasets with index features are relatively flat, which indicates that the influence caused by the number of feature is not significant. That is, the index features are more stable and suitable to distinguish ethnic groups.

Moreover, comparative analysis is also made in terms of average accuracy of different classifiers on all datasets. Table 16 shows that the average accuracy of the datasets with mixed features is higher than that of the datasets with other features, which imply that the selected mixed features are most discriminative for ethnicity recognition.

8 Conclusion

This paper utilizes manifold learning methods to investigate the structure of three Chinese ethnic groups' geometric facial features. Firstly, the geometric features are extracted according to conventional anthropometric definition, then used to conduct manifold analysis. The manifold structure analysis finds that these low-dimensional features can not generate



(a) PCA(male) **(b)** PCA(female)

Fig. 18 The manifold distribution of the dataset with mix features in low dimensional space

Table 10 J48

Dataset	Gender	TP rate	FP rate	Precision	Recall	F-measure	AUC
A	M	0.753	0.123	0.753	0.753	0.753	0.814
B	M	0.833	0.083	0.834	0.833	0.833	0.879
C	M	**0.92**	**0.040**	**0.921**	**0.920**	**0.920**	**0.935**
D	M	0.90	0.050	0.902	0.900	0.900	**0.935**
E	M	**0.960**	**0.020**	**0.960**	**0.960**	**0.960**	**0.975**
A	F	0.727	0.137	0.725	0.727	0.724	0.775
B	F	0.773	0.113	0.776	0.773	0.773	0.863
C	F	**0.813**	**0.093**	**0.814**	**0.813**	**0.812**	**0.853**
D	F	0.767	0.117	0.765	0.767	0.764	0.844
E	F	**0.813**	**0.093**	**0.818**	**0.813**	**0.814**	**0.888**

Table 11 Naive Bayes

Dataset	Gender	TP rate	FP rate	Precision	Recall	F-measure	AUC
A	M	0.820	0.090	0.821	0.820	0.820	0.927
B	M	0.900	0.050	0.903	0.900	0.901	0.960
C	M	0.960	0.020	0.960	0.960	0.960	**0.993**
D	M	**0.967**	**0.017**	**0.968**	**0.967**	**0.967**	0.992
E	M	**0.973**	**0.013**	**0.974**	**0.973**	**0.973**	**0.999**
A	F	0.773	0.113	0.779	0.773	0.772	0.882
B	F	0.753	0.123	0.755	0.753	0.750	0.902
C	F	**0.893**	**0.053**	**0.894**	**0.893**	**0.893**	0.947
D	F	0.887	0.057	0.889	0.887	0.887	**0.956**
E	F	**0.920**	**0.040**	**0.921**	**0.920**	**0.920**	**0.979**

Table 12 BayesNet

Dataset	Gender	TP rate	FP rate	Precision	Recall	F-measure	AUC
A	M	0.793	0.103	0.793	0.793	0.793	0.923
B	M	0.893	0.053	0.897	0.893	0.894	0.962
C	M	**0.967**	**0.017**	**0.967**	**0.967**	**0.967**	**0.995**
D	M	**0.967**	**0.017**	**0.967**	**0.967**	**0.967**	0.992
E	M	**0.987**	**0.007**	**0.987**	**0.987**	**0.987**	**1.000**
A	F	0.733	0.133	0.735	0.733	0.734	0.883
B	F	0.767	0.117	0.766	0.767	0.766	0.898
C	F	0.887	0.057	0.888	0.887	0.887	0.951
D	F	**0.900**	**0.050**	**0.901**	**0.900**	**0.900**	**0.964**
E	F	**0.913**	**0.043**	**0.914**	**0.913**	**0.913**	**0.983**

the sub-manifold structure of different ethnic groups' with semantic description. In order to validate whether facial geometric features can generate the sub-manifold structures for different ethnic groups, we expand the dimension of facial geometric features using detected 77 landmarks, and then mRMR feature selection is applied to filter out redundant features. Finally, the manifold structure analysis is conducted on the datasets with filtered distance-based, angular and index features. The experimental results show that the three groups of ethnic facial data can be well represented by the selected features. The sub-manifold structures of the three ethnic groups could be clearly generated based on the selected features, and the proposed indicator system can be utilized for effective ethnicity recognition. Despite the application in computational ethnic analysis, the proposed measurement indicator set can also enrich anthropology related research.

Finally, this paper could be summarized into the following conclusion. The index features are more crucial than distance-based and angular features in facial ethnicity representation. The mouth and facial shapes carry little ethnic facial feature, while the region that is consisted of eye,

Table 13 RGFNetwork

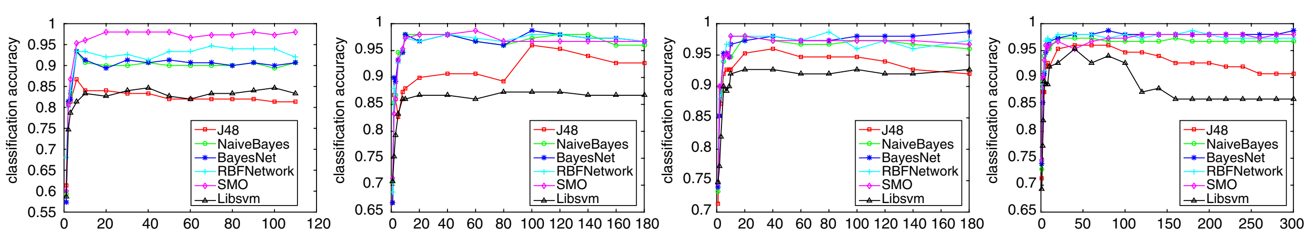
Dataset	Gender	TP rate	FP rate	Precision	Recall	F-measure	AUC
A	M	0.773	0.113	0.775	0.773	0.773	0.871
B	M	0.913	0.043	0.915	0.913	0.914	0.947
C	M	0.967	0.017	0.967	0.967	0.967	0.978
D	M	**0.973**	**0.013**	**0.974**	**0.973**	**0.973**	**0.976**
E	M	**0.993**	**0.003**	**0.993**	**0.993**	**0.993**	**0.994**
A	F	0.753	0.123	0.753	0.753	0.753	0.866
B	F	0.807	0.097	0.805	0.807	0.805	0.904
C	F	**0.900**	**0.050**	**0.900**	**0.900**	**0.900**	0.937
D	F	0.893	0.053	0.893	0.893	0.893	**0.943**
E	F	**0.907**	**0.047**	**0.909**	**0.907**	**0.907**	**0.940**

Table 14 SVM

Dataset	Gender	TP rate	FP rate	Precision	Recall	F-measure	AUC
A	M	0.773	0.113	0.775	0.773	0.772	0.830
B	M	0.820	0.090	0.823	0.820	0.823	0.865
C	M	0.860	0.070	0.858	0.860	0.857	0.895
D	M	**0.933**	**0.033**	**0.934**	**0.933**	**0.933**	**0.950**
E	M	**0.953**	**0.023**	**0.953**	**0.953**	**0.953**	**0.965**
A	F	0.733	0.133	0.752	0.733	0.734	0.800
B	F	0.720	0.140	0.758	0.720	0.713	0.790
C	F	0.667	0.167	0.715	0.667	0.608	0.750
D	F	**0.860**	**0.070**	**0.862**	**0.860**	**0.859**	**0.895**
E	F	**0.920**	**0.040**	**0.922**	**0.920**	**0.920**	**0.940**

Table 15 SMO

Dataset	Gender	TP rate	FP rate	Precision	Recall	F-measure	AUC
A	M	0.893	0.053	0.895	0.893	0.893	0.944
B	M	0.967	0.017	0.967	0.967	0.967	0.982
C	M	0.967	0.017	0.967	0.967	0.967	0.983
D	M	**0.973**	**0.013**	**0.974**	**0.973**	**0.973**	**0.985**
E	M	**0.973**	**0.013**	**0.973**	**0.973**	**0.973**	**0.985**
A	F	0.867	0.067	0.868	0.867	0.867	0.922
B	F	0.907	0.047	0.907	0.907	0.907	0.947
C	F	0.907	0.047	0.907	0.907	0.907	0.943
D	F	**0.933**	**0.033**	**0.934**	**0.933**	**0.934**	**0.965**
E	F	**0.953**	**0.023**	**0.954**	**0.953**	**0.953**	**0.970**



(a) Distance **(b)** Angle **(c)** Index **(d)** Mix

Fig. 19 The relation between the number of feature and classification accuracy using distance, angle, index and mixed feature

Table 16 Average

Gender	Feature	J48	Naive Bayes	BayesNet	RBF	SMO	SVM
M	20 distances	80.00	89.33	79.30	77.33	**89.33**	77.33
M	195 distances	83.33	90.00	89.33	91.33	**96.67**	82.00
M	250 angles	92.00	96.00	96.70	96.70	**96.70**	86.00
M	400 indexes	90.00	96.70	96.70	97.30	**97.30**	93.30
M	**51 filtered features**	**96.00**	**97.33**	**98.67**	**99.33**	**97.33**	**95.33**
F	20 distances	72.67	77.33	73.33	75.33	**86.67**	73.33
F	100 distances	77.33	75.33	76.67	80.67	**90.67**	72.00
F	250 angles	81.33	89.33	88.67	90.00	**90.67**	66.67
F	400 indexes	76.67	88.67	90.00	89.33	**93.33**	86.00
F	**51 filtered features**	**81.33**	**92.00**	**91.33**	**90.67**	**95.33**	**92.00**

nose and eyebrow is much more important for ethnic feature representation. Specifically, nosewing and the distance between eye and eyebrow are the most significant ethnic facial semantic indicators. In the future, the proposed representations in this paper will be extended to analyze facial feature of other ethnic groups.

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