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Learning Deformation Model for Expression-Robust 3D Face Recognition

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ABSTRACT

Expression change is the major cause of local plastic deformation of the facial surface. The intra-class differences with large expression change somehow are larger than the inter-class differences as it's difficult to distinguish the same individual with facial expression change. In this paper, an expression-robust 3D face recognition method is proposed by learning expression deformation model. The expression of the individuals on the training set is modeled by principal component analysis, the main components are retained to construct the facial deformation model. For the test 3D face, the shape difference between the test and the neutral face in training set is used for reconstructing the expression change by the constructed deformation model. The reconstruction residual error is used for face recognition. The average recognition rate on GavabDB and self-built database reaches 85.1% and 83%, respectively, which shows strong robustness for expression changes.

Keywords: 3D face recognition, facial deformation model, principal component analysis

1. INTRODUCTION

3D facial surface under expression change occurs varying plastic deformation, therefore, the spatial structure of 3D face model will change [1]. In the multi-expression face recognition research area, how to overcome or reduce the influence of facial expression, which means building expression weakening model, is a key issue in 3D face recognition.

Currently, the expression weakening face recognition methods can be divided into two categories: methods based on face rigid regions[2][3] and methods based on non-rigid area [4-6]. Due to the interference of the facial expression, face recognition method using rigid regions will get better performance than the method using the entire face. However, methods based on face rigid regions only use part of the face region, which will lose some significant information. Methods based on non-rigid region need first establishing a uniform model for all types of expression, and then computing corresponding expression parameters for test face. Since it's difficult to establish a unified expression model, the general idea of these method is using an approximate model, and reducing the expression distortion by the deformation model.

In this paper, an expression-robust 3D face recognition method is proposed by learning expression deformation model. The expression of the individuals on the training set is modeled by Principal Component Analysis (PCA)[1], the main components are retained to construct the facial deformation model. For the test 3D face, the shape difference between the test and the neutral face in training set is used for reconstructing the expression change by the constructed deformation model. The reconstruction residual error is used for face recognition. Experiments on GavabDB[7] and self-built database show the effectiveness of our methods compared with the existing four methods.

2. FACIAL DEFORMATION MODEL

Facial deformation model [6] is a commonly used 3D face modeling method. In face modeling area, automatic modeling of realistic 3D face is based on a priori knowledge of a number of face prototypes. In Gong's method[8], a neutral face model can be got by training all the neutral faces in the library, and the multi-expression test face is used to reconstruct a simulated neutral face in the neutral face model space. In this paper, we construct the expression

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deformation prototype model using 3D multi-expression faces, in order to achieve linear operation between all kinds of facial expressions. Generally, a linear combination of all types of multi-expression faces can generate a new face with arbitrary expression. However, the dimension of the prototype face is generally high, and there is some correlation between the different facial expressions, therefore, in this paper, we proposed to use PCA for dimension reduction to expression vectors of deformation model.

2.1 System Description

3D face recognition problem can be defined as follows, there are two faces for each individual registered in gallery, one is neutral, the other is the expression change, for a probe with expression change, how to achieve the correct identification.

We divide the face into two components, the basic facial shape component (BFSC) and expressional shape component (ESC). BFSC can be understood as a neutral face. We parametrically define the shape differences caused by facial expression changes based on the difference between neutral face and expressional face. $\Delta R = F_{\exp ression} - F_{neutral}$ represents the expression change of face. $F_{\exp ression}$ indicates the expressional face, and $F_{neutral}$ indicates the neutral face.

We proposed an expression robust 3D face recognition method. The entire process including 3D facial data acquisition, pre-processing, pose registration and face deformation model establish using PCA.

2.2 Facial Deformation Model

In our proposed expression robust recognition method, different expressions of the same person are analyzed by principal component analysis to obtain the expression subspace, referred to as facial deformation model. The pose, size of every face must be standardized firstly to apply PCA. In this paper, based on the principal component analysis, all faces should be registered with a standard front face, and then re-sampled in the xoy plane with a rectangular grid. The depth of each grid is taken by the average depth value of all the vertices fall within the sampling grid. After resampling, all 3D faces are unified representation, the size is $H * W$, and all frontal. The specific process for proposed facial deformation model construction is shown as follows:

1. Compute the expressional vector of the ith person, $R_i = F_{Ei} - F_{Ni}$,where F_{Ni} , F_{Ei} represents the neutral face and expressional face of the ith person.

2. Compute the average value μ of the face set $\{R_1, R_2, \ldots, R_M\}$, where R_i shows the expression vector of each person.

3. Structure $A = \{\phi_1, \phi_2, \ldots \phi_M\}$, each column vector is $\phi_i = R_i - \mu$, which means the residual vector of training expression vector and the average.

4. Compute covariance matrix $C = AA^T$ and the first K （$K < M$） eigenvalues and eigenvetors of covariance matrix C. The matrix comprised by the eigenvectors is M , called facial deformation model.

The matrix M after PCA transform can be considered as the best feature vector matrix which represents the facial deformation model. Figure 1 shows the eigenvectors in matrix M changing with the eigenvalues from large to small.

In Fig.1, from left to right shows eigenvectors corresponding to the first, second, third, ninth, tenth, eleventh, twenty-fifth, twenty sixth, and twenty seventh largest eigenvalues. It can be found the relationship between facial expression changes and the eigenvectors. Eigenvectors corresponding to the first three largest eigenvalues mainly reflects the wide range of expression changes around mouth and cheek. With eigenvalues decrease, the eigenvectors reflect a small range of expression change, such as eyebrows, eyes, nose and forehead. It is worth mentioning that eigenvector corresponding to the maximum eigenvalue performance in the mouth and lower jaw. The eigenvector corresponding to the second highest eigenvalue reflects expression change regions, also extended to nose region, meanwhile offset to cheek.

Figure 1. Eigenvectors in expression deformation space

2.3 Matching Based on Reconstruction Errors

For a test face F_{test} , it is needed to be normalized and transformed to coordinate system of the gallery set. The shape difference between test face and gallery, noted as $R^{i}{}_{test}$ $(i = 1,2 \ldots M)$, can be computed by Equation (1). Only when the test face and the training face represents the same person, the shape difference between those is the expression difference. Based on the facial deformation model, $R_{p}{}^{i}{}_{test}$ could be reconstructed using $R^{i}{}_{test}$, shown in Equation (2). Equation (3) defines the reconstruction error.

$$R^{i}{}_{test} = F_{test} - F_{Ni} \tag{1}$$

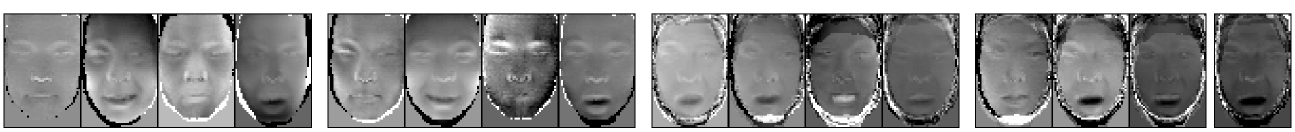
$$R_{p}{}^{i}{}_{test} = M(M^{T}M)^{-1}M^{T}E^{i}{}_{test} \tag{2}$$

$$e^{i} = R_{p}{}^{i}{}_{test} - R^{i}{}_{test} \tag{3}$$

where F_{Ni} means the neutral face of the i[th] person, F_{test} is a test face, M is the facial deformation model. $E^{i}{}_{test}$ is the shape difference between test face and the neutral face in galley. e^{i} is the reconstruction error for the i[th] person.

For face recognition, the reconstructed expression residual can be discriminated by using the correlation coefficient as the similar measure estimation. The smaller error represents closer reconstructed expressional face, as a result, the test face should be classified to that class.

Distance or similarity measure is calculated by computing the expression vector of the test face and template face in database, and then sorted for all faces in the database according to this distance or similarity measure. The sorted value is recorded as the output of the test face. The most similar template is definitely as the first candidate.



(a) Same expression (b) Different expressions (c) Reconstructed same expression (d) Reconstructed different expressions

Figure 2. Expression reconstruction results

After we get the reconstructed expression feature vectors, the correlation coefficient can be used as the similarity measure criterion. From Fig.2, it can be found that the inter-class difference and intra-class difference has large diversity. intra-class difference caused by expression mostly occurs in the mouth, eyebrow, lower cheek, whereas inter-class difference is unstable as any region of face could cause the inter-class change .

3. EXPERIMENTAL RESULTS

3.1 3D Face Database

In this paper, algorithm performance comparison experiments are based on GavabDB [7] and self-built database. Both database include facial expression change. In 2.94GHz CPU, 1.95GB memory of the PC and VS2008 test environment. GavabDB includes 61 individuals, and contains two kinds of expression, smile and laugh. Our Lab also built an small 3D multi-expression face database using the Minolta Vivid 910 laser scanner, comprising 48 individuals, 7 different facial expressions, such as smile, laugh, disgust, fear, surprise, sad, and anger.

To test the expression robust of the compared methods, here we use the leave-one-out (LOO) cross validation. Gallery include a neutral face and an expressional face, the rest multi-expression faces together as test set.

3.2 Experimental Results on GavabDB

For GavabDB, smile and laugh were selected as the training face, other faces as the test set. The experimental results are shown in Table 1, the average recognition rate reached 85.1%.

It can be found from Table 1, the recognition rate of the proposed method is slightly lower than Peng's[9] method, but much better than Mahoor's [10] and Moreno's [11,12]. For 3D face, although the curvature of each vertex contains surface geometric information, but the fusion feature definitely represents more distinguishable information and can get the higher recognition rate[9]. In Moreno's [11] method, error of shape matching will large when the facial shape has large distortion by expression, which means the recognition rate will decrease. In Moreno's experiments[11], the Rank-one recognition rate changes about 14% from smile to laugh.

We also compare the algorithm efficiency of Mahoor's [10], Peng's[9] and our proposed method. As Mahoor's method[10] and Peng's method[9] both includes the feature extraction process, which is time-consuming. Furthermore, the error in feature extraction process will affect the final recognition rate. Our method doesn't need the feature extraction process and directly use the PCA for facial deformation model construction which greatly improves the efficiency. From Table 2, it can be seen that, our method has higher efficiency, only 0.4s for single recognition.

Table 1. Rank-one recognition rate results on GavabDB with expression change.

Expression	Peng's [9]	Mahoor's [10]	Moreno's [11]	Moreno's [12]	**Ours**
Smile	86%	82%	62%	77.9%	**85.7%**
Laugh	85%	73.8%	48%		**84.5%**

Table 2. Algorithm efficiency on GavabDB.

Method	**Time for single recognition(Unit: s)**
Mahoor's[10]	1.275
Peng's [9]	1.051
Ours	0.4

3.3 Experimental Results on self-built database

For the self-built database, we select one type of the 7 expressions as the training face, the others together as the test set. The experimental results are shown in Table 3, the average recognition rate is 83%.

Table 3. Recognition rate for different expressions on the self-built database

Method	**smile**	**laugh**	**disgust**	**fear**	**surprise**	**sad**	**anger**
Ours	80.6%	83.0%	82.0%	85.1%	85.1%	85.0%	80.2%

From Table3, it can be found that the recognition rates for fear, surprise and sad are all above 85%, whereas for the smile and anger expression, the recognition rates are quite low, about 80%. Therefore, the impact on 3D face shape of different expression has different levels. By analyzing facial expressions, it can be found that in the state of fear, surprise and sad, there will have large range of shape deformation around eyes and mouth, as well as the nose and cheek. While for the smile and anger expression, the facial deformation is small, only has a slight deformation in the mouth region.

This difference indicates that facial deformation model constructed by expressions which cause large shape deformation will have better generalization, hence the recognition rate is higher.

Figure 3 shows the recognition rate under a single training expression tested by different expressions, specifically. Basically, if the training expression has large shape deformation, such as fear, surprise, and sad, recognition rate of all kinds of expressions can reach about 85% with less fluctuation. When using smile as the training expression which only causes small shape deformation, recognition rates of all kinds of expression test have fluctuant changes, fluctuation range is higher more than 30%.

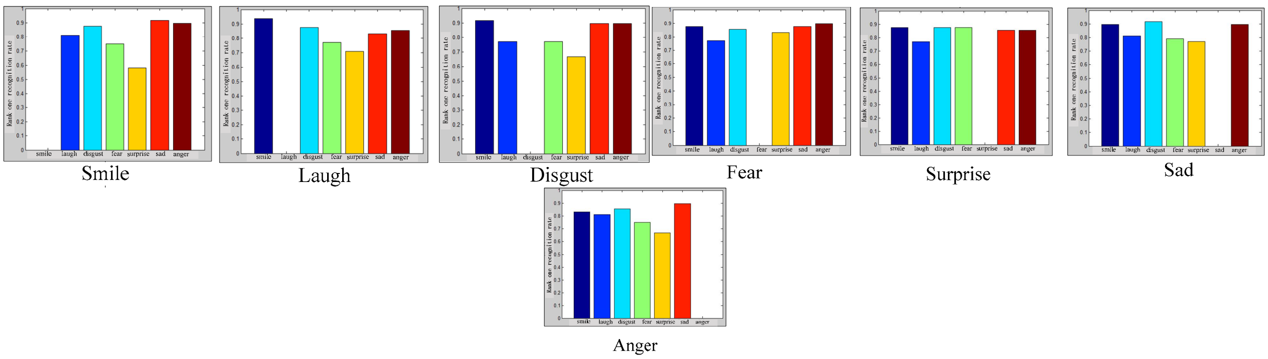


Figure 3. Rank-one recognition rate on different expressions by training the same expression sample

4. CONCLUSION

This paper presented an expression robust 3D face recognition method using a facial expression deformation model which can weaken the expression effect. First, all expressions in the training set were modelled by PCA method, the retaining main component formed the final facial deformation model. For the test expressional face, using the shape different between it and the neutral face in training library for reconstruction based on the facial deformation model. Finally, according to the reconstruction error for recognition. On GavabDB database, the average recognition rate of our proposed method researched 85.1%, compared with other methods, the results show that our method has advantages in recognition and performance. Meanwhile, the average recognition rate of self-built database contains seven expressions reached 83%, indicating that the method proposed in this paper is robust to expression change.

5. ACKNOWLEDGEMENT

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