H-035

The Research of 3D Face Recognition Based on Local Feature Matching

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1. Introduction

As one of the most promising and challenging branches in biometric recognition technology, face recognition has been received significant attention, especially during the past decades. Comparing with the other commonly used biometric recognition technologies, such as fingerprint and iris recognition, face recognition gains an advantage over them. Though Iris recognition is extremely accurate, yet it is considerably expensive to implement and not very accepted by people. Fingerprint recognition is reliable and non-intrusive, but not suitable for non-collaborative individuals. By contrast, face recognition seems to be a good compromise between reliability and social acceptance as well as the balance between security and privacy. It is considered to be user-friendly and apt to be accepted by people.

Though 2D face recognition has been made great progress in the past two decades, and achieved good performance under certain constrained conditions, it is still encountered with challenges of variations in illumination, facial pose and expression. In view of the fact that 2D image is essentially a projection of the 3D object onto 2D space. Compared with the 2D face image, the 3D face data contains more spatial information, which is inherent property of the face and is robust to uncontrollable environments where 2D appearance can be affected. So, 3D face recognition is deemed to bring the dawn to overcome this dilemma. With the development of 3D information acquisition technologies, such as laser scanner, structured light and stereo vision, it is likely and convenient to acquire the 3D data of an object. Consequently, utilizing 3D shape information for face recognition is attracting more and more attention in recent years [1].

2. Preprocessing of 3D Facial Data

3D data registration is a crucial and indispensable stage for the performance of the whole system [2]. Its purpose is to align different 3D face image into a normalization coordinate system to remove the influence of pose variations.

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According to anatomy evidence, the nose region has several advantages intuitively compared to the whole face region. So, the nose tip is first coarsely located, and then this position is considered as a sphere center for cropping facial region, as shown in Fig. 1.

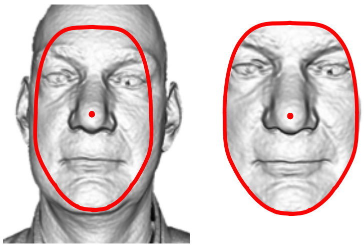

Fig.1: Trimmed facial region

In order to create an intrinsic coordinate system, K-L transformation is implemented to adjust coordinate system. At first, we approximately determine the location of nose tip [3] and view this position as datum mark. And then, select points within the range of r and construct local points set $P=\left\{p \middle| f\left(p_i,p_o\right)\le r\right\}$, where p_o and $f\left(p_i\ ,p_o\right)$ indicate the nose tip and Euclidean distance function, respectively.

Next, construct a covariance matrix of this point set, and carry out K-L transformation.

$$E_p=\frac{1}{N}\sum_{i=0}^{n-1}p_i\,,\ i=0,1,\cdots,n-1 \tag{1}$$

$$cov\,P=\frac{1}{N}\sum_{i=0}^{n-1}(p_i-E_p)(p_i-E_p)^T \tag{2}$$

$$cov\,P\times v_i=\lambda_i v_i \tag{3}$$

We will get three eigen-values $\lambda_1\ge\lambda_2\ge\lambda_3$ and their corresponding eigenvectors v_1 , v_2 , v_3 . Taking v_1 , v_2 and v_3 as three main axes, a new coordinate system can be established, just as illustrated in Fig. 2.

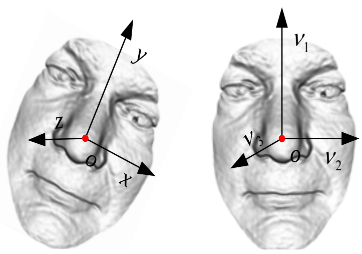

Fig.2: Adjusting coordinate system

And then, executing translation and rotation transform, the point set P_{fi} in the new coordinate system can be obtained.

$$P_{ni} = (p_i - p_n),\ i = 0,1,\cdots,n-1 \tag{4}$$

$$U = \begin{pmatrix} v_1 & v_2 & v_3 \end{pmatrix}^T \\ P_{fi} = P_{ni} \times U^{-1},\ i = 0,1,\cdots,n-1 \tag{5}$$

3. Fitting Facial Surface by B-splines Approximation

Since the original 3D face data are represented by a large number of space scattered points, it does not possess spatial structure information. To investigate face features for further research, it is especially necessary to fit a face model based on the obtained point set P_{fi} in ROI (region of interest), which should be easily described and provided with richer characteristic information of human.

For a given set of scattered points $P = \{(x, y, z)\}$ in ROI, considering a rectangular domain $\Omega = \{0 \le x \le m,\ 0 \le y \le n\}$ in the xoy-plane, and assuming (x, y) is an arbitrary point in Ω. To approximate the scattered data P, we might as well construct an $m \times n$ lattice which spans a uniform grid in Ω, and define the lattice by a controlled lattice Φ overlaid on the domain Ω. Let ϕ_{ij} be the value of the ij-th control point on lattice Φ, through the control points, the approximation function [4] can be expressed as:

$$F(x,y) = \sum_{k=0}^{3}\sum_{l=0}^{3} B_k(s) B_l(t) \phi_{(i+k)(j+l)} \tag{6}$$

$$B_0(t) = (1-t)^3/6,\ B_1(t) = (3t^3 - 6t^2 + 4)/6 \tag{7}$$

$$B_2(t) = (-3t^3 + 3t^2 + 3t + 1)/6,\ B_3(t) = t^3/6 \tag{8}$$

Here, $i = \lfloor x \rfloor - 1$, $j = \lfloor y \rfloor - 1$, $s = x - \lfloor x \rfloor$, $t = y - \lfloor y \rfloor$, B_k and B_l are the basis functions of the uniform cubic B-splines.

So as to accurately approximate the scattered data, the key of this problem is changed into solving for the control points in Φ. According to the principle of least squares, it is not difficult to get $\phi_{(i+k)(j+l)} = w_{kl} z_c \Big/ \sum_{a=0}^{3}\sum_{b=0}^{3} w_{ab}^2$. Since the obtained ϕ_{ij} is not unique, we denote the error by $e(\phi_{ij}) = \sum \left(w_{kl}\phi_{lk} - w_{kl}\phi_{ij} \right)^2$ and make it be minimal value to find out the optimal ϕ_{ij}. Namely, by differentiating $e(\phi_{ij})$ with respect to ϕ_{ij} and let it be zero, we will get the final $\phi_{ij} = \sum_c w_{kl}^2 \phi_{kl} \Big/ \sum_c w_{kl}^2$.

Performing the same operation for the whole scattered points, a relatively accurate facial surface can be achieved.

4. Recognition Based on Local Features Matching

It is well known that human facial expressions are extremely rich, and the facial differences between different individuals are not very distinct. Meanwhile, the differences of the same individual due to facial expression changes are often greater than the facial differences between different individuals, which results in tremendous challenge for face recognition. To address this challenge, we should enlarge the facial differences between different individuals as much as possible, and extract the features which are immune to variations in illumination, pose and expression to carry out face recognition.

4.1 Extracting Locally Rigid Face Region

After completing the fitting facial surface, we project it onto the *xoy*-plane and select some rigid face regions which can strongly resist expression changes. And then, mark a number of feature points on it. So as to make recognition performance more robust, those locally rigid facial patches are extracted, as shown in Fig. 3.

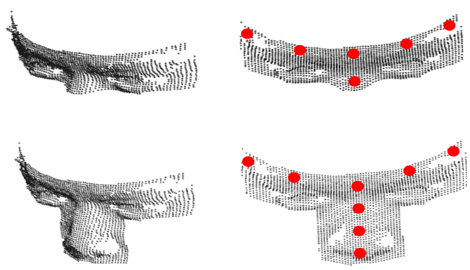

Fig. 3: Extracting local rigid facial patches

4.2 Calculating the Curvatures of Feature Points

When the above-mentioned work is finished, the curvature calculation of feature points can be launched on. For 3D face, it is no doubt that the curvature of facial surface is the essential feature, and it is independent of pose variation. In view of the fact that Gaussian curvature K is the intrinsic metric value of curvature, and the mean curvature H describes the curved measurement of the surface at the point. For this reason, the curvatures of local facial surface patches which are insensitive to expression variations are employed to perform recognition matching [5].

According to the expression （6）, differentiating $F(x,y)$ with respect to x and y respectively, we will solve for the first order derivatives, the second order derivatives and the mixed partial derivative. Herein, only list the expressions of $f_x(x,y)$, $f_{xy}(x,y)$ and $f_y(x,y)$

$$\begin{aligned} f_x(x,y) &= \sum_{k=0}^{3}\sum_{l=0}^{3} B_k^{'}(s) B_l(t)\phi_{(i+k)(j+l)} \\ f_{xy}(x,y) &= \sum_{k=0}^{3}\sum_{l=0}^{3} B_k^{'}(s) B_l^{'}(t)\phi_{(i+k)(j+l)} \\ f_y(x,y) &= \sum_{k=0}^{3}\sum_{l=0}^{3} B_k(s) B_l^{'}(t)\phi_{(i+k)(j+l)} \end{aligned} \tag{9}$$

Writing the extracted patches in the form of vector $r(x,y)=[x,y,f(x,y)]$, and performing the operation of derivation, we can get

$$\begin{aligned} & r_x=[1,0,f_x], r_y=[0,1,f_y], r_{xx}=[0,0,f_{xx}], r_{xy}=[0,0,f_{xy}] \\ & r_{yy}=[0,0,f_{yy}],\ n=\frac{r_x\times r_y}{|r_x\times r_y|}=\frac{1}{\sqrt{f_x^2+f_y^2+1}}[-f_x,-f_y,1] \end{aligned} \tag{10}$$

Denote the first basic quantities by $E, F\ and\ G$ and the second basic quantities by $L, M\ and\ N$, further proceeding to calculation, we will have

$$\begin{aligned} & E=r_x\cdot r_x=1+f_x^2, F=r_x\cdot r_y=f_x f_y, G=r_y\cdot r_y=1+f_y^2 \\ & L=\frac{f_{xx}}{\sqrt{f_x^2+f_y^2+1}}, M=\frac{f_{xy}}{\sqrt{f_x^2+f_y^2+1}}, N=\frac{f_{xy}}{\sqrt{f_x^2+f_y^2+1}} \end{aligned} \tag{11}$$

Consequently, Gaussian curvature K and mean curvature H can be obtained.

$$K=\frac{LN-M^2}{EG-F^2} \tag{12}$$

$$H=\frac{LG-2MF+NE}{2(EG-F^2)} \tag{13}$$

Taking the locally facial patch of the bridge of nose as an example, the curvature of feature points are given out in the following two tables.

Table 1: Curvature vector of ten different subjects in the same mode

ID	The curvature of feature points			
	forehead	nose tip	chin	lip
1	.035167	.031332	.050966	.03787
2	.043937	.034244	.048843	.037738
3	.041539	.031103	.044541	.03927
4	.040938	.034479	.027915	.038874
5	.043052	.031287	.055814	.041817
6	.051872	.034703	.047945	.036829
7	.047494	.037765	.042662	.03541
8	.044561	.034384	.036464	.042822
9	.048932	.045562	.035547	.037656
10	.036094	.035358	.033774	.034741

Table 2: Curvature vector of one subject in different expression modes

ID	The curvature of feature points			
	forehead	nose tip	chin	lip
201	.043937	.034244	.048843	.037738
202	.047016	.030391	.041866	.040268
203	044362	.035408	.052266	.039206
204	.04107	.034878	.046809	.037326
205	.043609	.029023	.054784	.039775

4.3 Constructing Feature Vectors

According to the calculated curvature value of feature points, we construct a set of feature vectors, and associate these vectors with the original 3D face, and then set up the corresponding map. Through comparing feature vectors, the final recognition can be achieved.

5. Experiments and Discussions

During the course of ding experiments, we employed the CASIA 3D Face Database. The database consists of 4624 scans of 123 subjects and each subject contains 37 or 38 scans. By using a non-contact 3D digitizer-Minolta Vivid 910, these 3D data are captured under different conditions including variations of illumination, facial pose and expression [6].

To evaluate recognition performance of the proposed algorithm, a series of experiments are carried out. In our experiments, only ten persons are taken into account.

In the process of recognition, the strategy of multi-level recognition is adopted. It is obvious to see that the recognition rate is remarkably improved with the increasing of rank. The corresponding CMC (cumulative match characteristic) curve is shown in Fig. 4.

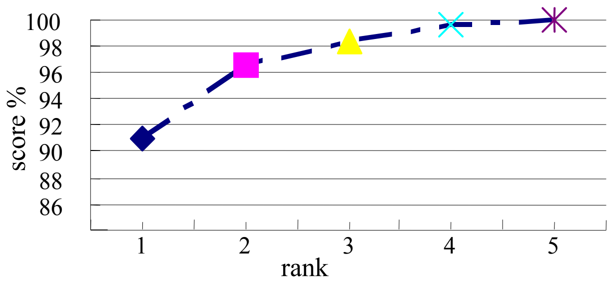

Fig. 4: The CMC curve of the presented method

It is easy to see that the recognition rate of rank-1 and rank-2 are 91% and 96.5%, respectively, which sufficiently indicate that the proposed method based on local curvature feature matching for 3D face recognition is effective and promising.

6. Conclusions and Future Works

In this paper, an approach based on local curvature feature matching for 3D face recognition is proposed. Comparing with the conventional PCA-based method, the recognition rate is distinctly enhanced. Through analyzing the curvature features of locally rigid facial patches, we performed a series of experiments based on the part of CASIA 3D Face Database. The experimental results demonstrate high performance of our presented method and also show that the approach is fairly effective for 3D face recognition.

In view of the fact that the location of feature points is difficult to accurately registration, the robustness of the proposed approach lacks of good adaptability to some extent. As to future work, on one hand, we should make great efforts to seek some ways which can be automatically accurate locate the positions of feature points. On the other hand, we need to execute experiments in a larger scale of database to further verify the feasibility of the proposed methods.

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