1-1-2011

3D face recognition based on a modified ICP method

Kankan Zhao
University of Wollongong, kz989@uowmail.edu.au

Jiangtao Xi
University of Wollongong, jiangtao@uow.edu.au

Yanguang Yu
University of Wollongong, yanguang@uow.edu.au

Joe F. Chicharo
University of Wollongong, chicharo@uow.edu.au

3D face recognition based on a modified ICP method

Abstract

3D face recognition technique has gained much more attention recently, and it is widely used in security system, identification system, and access control system, etc. The core technique in 3D face recognition is to find out the corresponding points in different 3D face images. The classic partial Iterative Closest Point (ICP) method is iteratively align the two point sets based on repetitively calculate the closest points as the corresponding points in each iteration. After several iterations, the corresponding points can be obtained accurately. However, if two 3D face images with different scale are from the same person, the classic partial ICP does not work. In this paper we propose a modified partial Iterative Closest Point (ICP) method in which the scaling effect is considered to achieve 3D face recognition. We design a 3x3 diagonal matrix as the scale matrix in each iteration of the classic partial ICP. The probing face image which is multiplied by the scale matrix will keep the similar scale with the reference face image. Therefore, we can accurately determine the corresponding points even the scales of probing image and reference image are different. 3D face images in our experiments are acquired by a 3D data acquisition system based on Digital Fringe Projection Profilometry (DFPP). A 3D database consists of 30 group images, three images with the same scale, which are from the same person with different views, are included in each group. And in different groups, the scale of the 3 images may be different from other groups. The experiment results show that our proposed method can achieve 3D face recognition, especially in the case that the scales of probing image and referent image are different.

Keywords

face, recognition, based, modified, ICP, method

Disciplines

Physical Sciences and Mathematics

Publication Details

Zhao, K., Xi, J., Yu, Y. & Chicharo, J. F. (2011). 3D face recognition based on a modified ICP method. 2011 International Conference on Optical Instruments and Technology: Optoelectronic Imaging and Processing Technology (pp. 82000G-1-82000G-11). Bellingham, Washington: SPIE.

3D Face recognition based on a modified ICP method

Kankan Zhao[1,a], Jiangtao Xi[1,b], Yanguang Yu*[1,c], Joe F. Chicharo[1,d]

[1]School of Electrical, Computer and Telecommunications Engineering, University of Wollongong, Northfields Ave, Wollongong, NSW, 2522, Australia

E-mail: [a]kz989@uowmail.edu.au, [b]jiangtao @uow.edu.au, [c]yanguang@uow.edu.au

ABSTRACT

3D face recognition technique has gained much more attention recently, and it is widely used in security system, identification system, and access control system, etc. The core technique in 3D face recognition is to find out the corresponding points in different 3D face images. The classic partial Iterative Closest Point (ICP) method is iteratively align the two point sets based on repetitively calculate the closest points as the corresponding points in each iteration. After several iterations, the corresponding points can be obtained accurately. However, if two 3D face images with different scale are from the same person, the classic partial ICP does not work. In this paper we propose a modified partial Iterative Closest Point (ICP) method in which the scaling effect is considered to achieve 3D face recognition. We design a 3×3 diagonal matrix as the scale matrix in each iteration of the classic partial ICP. The probing face image which is multiplied by the scale matrix will keep the similar scale with the reference face image. Therefore, we can accurately determine the corresponding points even the scales of probing image and reference image are different. 3D face images in our experiments are acquired by a 3D data acquisition system based on Digital Fringe Projection Profilometry (DFPP). A 3D database consists of 30 group images, three images with the same scale, which are from the same person with different views, are included in each group. And in different groups, the scale of the 3 images may be different from other groups. The experiment results show that our proposed method can achieve 3D face recognition, especially in the case that the scales of probing image and referent image are different.

Keywords: 3D face recognition, ICP, scale difference.

1. INTRODUCTION

Face recognition technique is one of the biometric techniques used in access control system, surveillance system, credit card payment system, etc. Face recognition based on 2D face images has already developed maturely and [1] gives a good literature survey of the recent 2D face recognition technique. 3D face recognition technique appears the late of last century and has been utilized widely during these days. Although 3D images are more complicated than 2D images, they are invariant in illumination and accurate in geometric information. Range images are a kind of 3D images. A range image (depth map) comprises a 2D matrix, and each element in the matrix reflects the distance of one point on the object surface to the camera. Range images provide plenty of geometric information for 3D face recognition and invariant in different lighting conditions and viewpoints.

Some recent literature surveys for 3D face recognition can be found in [2, 3]. Iterative Closest Point (ICP) is one of the classic algorithms in 3D face recognition. It was proposed first by Chen et al. [4] and Besl et al. [5]. ICP method finds out the motions from the corresponding point pairs between two point sets in order to align two point sets. To find out the

2011 International Conference on Optical Instruments and Technology: Optoelectronic Imaging and Processing Technology, edited by Toru Yoshizawa, Ping Wei, Jesse Zheng, Proc. of SPIE Vol. 8200, 82000G · © 2011 SPIE · CCC code: 0277-786X/11/$18 · doi: 10.1117/12.906570

corresponding points from the reference image to the probing image, Chen et al. [4] in 1991 were using the distance from the points on the reference to the tangent planes on the probing image while Besl et al. [5] in 1992 directly searched the closest points from reference to probe. But both of them cannot deal with gross outliers, occlusion, appearance and disappearance[6]. In 1994, Zhang [6] proposed partial ICP which sets an adaptive distance threshold for corresponding points selection for every iteration, so that the unreasonable point pairs can be discarded. Therefore, it is easy to solve gross outliers, occlusion, appearance and disappearance.

However, if two 3D face images with different scales are from the same person, the classic ICP does not work. In 2000, Zha el al. [7] utilized the extended signature images to establish correspondence between two images no matter these two images are in the same scale or not. Zinßer et al. [8] estimated a scale factor between the two point sets in every iteration in 2005. At the same time, Ko et al. [9] used the ratio of the normal curvatures on two point sets as the scale factor. In 2010, Du et al. [10] took a 3×3 scale matrix into account in the Least Squares (LS) problem with a constraint condition. This paper proposes a 3D face recognition method based on a modified partial ICP. Our proposed method divided into two steps: coarse alignment and fine alignment. In coarse alignment, we use three feature points to get an initial estimation. In fine alignment, we integrate a 3×3 scale matrix into partial ICP in order to solve the scale difference problem.

The rest of this paper is organized as follows: section 2 introduces our data acquisition system and database, section 3 gives an initial estimation for coarse alignment, section 4 explains the partial ICP and scale matrix computation, section 5 gives the experiment results and section 6 is the conclusion.

2. DATA ACQUISITION SYSTEM AND DATABASE

2.1 Data acquisition system

The 3D face data can be collected by a 3D data acquisition system based on Digital Fringe Projection Profilometry (DFPP). DFPP based system is an effective system of the non-contact 3D shape measurement system, which belongs to the Structured Light Projection Profilometry (SLPP) data acquisition system. A DFPP based data acquisition system contains a CCD camera, a digital video projector and a computer. Fig. 1. and Fig. 2. are the sketches of our data acquisition system.

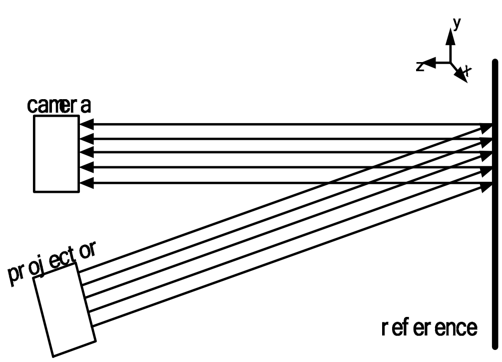


Fig.1. the Structure of Fringe Patterns Projected onto the Reference Plane

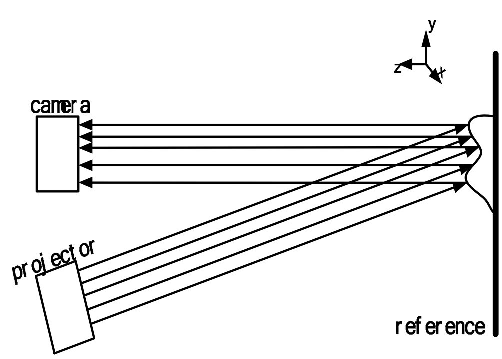
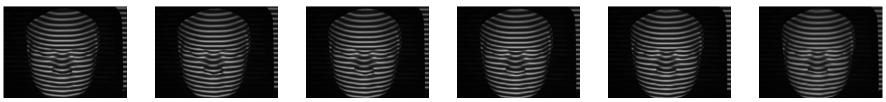


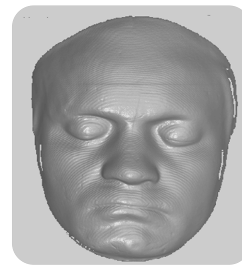
Fig. 2. the Structure of Fringe Patterns Projected onto the Object

The DFPP data acquisition system projects one group of well-designed fringe patterns on two surfaces: the reference plane and the probing object. The fringe patterns on the object will have deformations compared with the fringe patterns projected on the reference. A CCD camera is needed to capture the two groups of fringe patterns, after analyzing the deformation of two groups fringe patterns, the height from the probing object surface to the reference plane can be figured out. In order to get a better reconstruction result, we decide to use 6 frequencies of fringe patterns in one group. Fig. 3. is the reconstruction procedure of DFPP data acquisition system. Fig. 3.(a) is the 6 frequencies fringe patterns projected on the reference plane, Fig. 3.(b) is the 6 frequencies fringe patterns projected on the probing object, Fig. 3.(c) is the reconstruction result after the height computation. Because of the advanced developed digital projection technology these years, the DFPP based system is used widely because of its simple structure and efficiency cost [11].

(a) The 6 frequencies fringe patterns projected onto the reference plane.



(b) The 6 frequencies fringe patterns projected onto the probing object.



(c) The reconstruction result

Fig. 3. the reconstruction procedure of DFPP data acquisition system

2.2 3D database

Based on our DFPP data acquisition system, we build a small size 3D face database. Our database consists of 30 group images. In each group, there are three images with the same scale, which are from the same person with different views (frontal, left and right view). And in different groups, the scale of the 3 images may be different from other groups. Fig. 4. gives an example when our system is acquiring the face data. Fig. 5. is one 3D face image in our database. In each image, we have over 100,000 points to describe a human face.

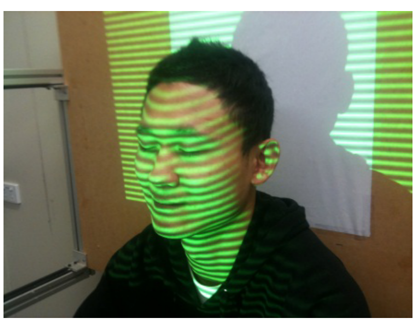


Fig. 4. Real face data acquisition.

Fig. 5. An example 3D face image in our database.

3. COARSE ALIGNMENT

3.1 Feature points selection

Rotation matrix R, translation matrix t and scale matrix s need to be set as the initial estimation in our proposed method. In our data acquisition system, we manually select three 7×7 regions as the candidate feature points on every face images. The three regions are the right corner of the left eye, the left corner of the right eye and nose tip.

Once the candidate feature point regions are decided, we compute the shape index for every points in the 7×7 region, and between the corresponding 7×7 region of reference face image and probing face image, the two corresponding feature points can be selected if the two points on the reference and probe have the closest shape index value. The shape index at point p is calculates by using the maximum (k_1) and minimum (k_2) curvatures.

$$\mathrm{SI(p)} = \frac{1}{2} - \frac{1}{\pi}\tan^{-1}\frac{k_1(p)+k_2(p)}{k_1(p)-k_2(p)} \quad (1)$$

Equation (1) gives the detail of how to calculate the shape index at a given point p. From the equation, we can get the shape index value at any arbitrary point is in the interval $[0,1]$.

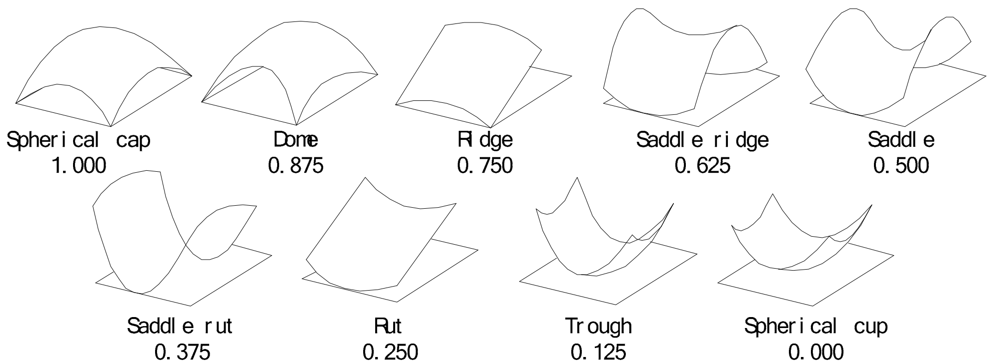


Fig. 6. nine shape types on shape index scale[12].

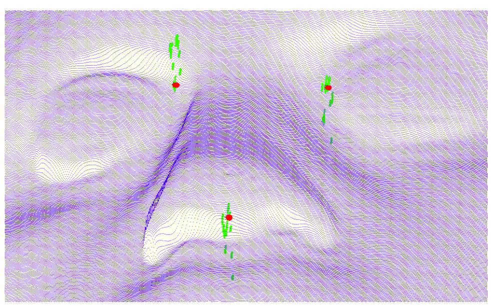


Fig. 7. the 3 feature points selected by our method

Fig. 6. gives the nine shape types and their shape index value. Fig. 7. is the feature points selected by our method. The green area is the candidate feature points, the three red points are the feature points after the analysis of the curvatures.

3.2 Initial values computation

Once the feature points are selected, the rotation, translation and scale can be calculated. We use dual quaternions method to compute the motion. It will be described in the next section.

For feature points on the probing face image m and feature points on the reference face image r, the covariance matrices C_m *and* C_r of m and r can be calculated. We can get the scale factor for the two data sets:

$$S_{ini} = \frac{1}{3}\sum_{i=0}^{3}\frac{\mu_j}{\lambda_j}\ (\mathrm{j} = 1{,}2{,}3.) \quad (2)$$

Where λ_j is the square root of the j-th eigenvalues of C_m, μ_j is the square root of the j-th eigenvalues of C_r.

Here we set a scale boundary for fine alignment because we cannot avoid the situation that one point set convergence to the subset of the other point set [10]. Hence the scale boundary becomes to:

$$S_{ini} - \delta < \mathrm{S} < S_{ini} + \delta \tag{3}$$

where δ is a threshold set by the user.

We denote a = $S_{ini} - \delta$ and b = $S_{ini} + \delta$.

4. FINE ALIGNMENT AND MATCHING

4.1 Partial ICP

For fine alignment, we selected partial ICP [6] as the framework. Partial ICP is iteratively align two point sets which overlapped partially based on repetitively calculate the closest points as the corresponding points in each iteration. After several iterations, the corresponding points can be obtained accurately.

Distance distribution is used to decide a distance threshold between the reasonable point pairs and unreasonable point pairs. This distance threshold is the key to deal with outliers, occlusion, appearance and disappearance in partial ICP [6]. It can handle the situation that part of probing point set overlaps part of the reference point set. The brief conclusion of partial ICP is given below.

The object function of partial ICP is

$$\mathcal{F}(\mathrm{R},\mathrm{t}) = \frac{1}{\sum_{i=1}^{m} p_i} \sum_{i=1}^{m} p_i d^2(Rx_i + t, D'). \tag{4}$$

Where x_i is the i-th point in the probing image, m is the number of point in the probing image. R is the rotation matrix (3×3) and t is the translation matrix (3×1) between probing image and reference. D' is the reference image, $d^2(Rx_i + t, D')$ is the square of the distance from point x_i to the surface D'. p_i could be 0 or 1. If x_i can be matched to one point in D', p_i takes 1, otherwise p_i takes 0.

In partial ICP, a tolerance distance D_{max} is set for selecting the matched point pairs. For example, we have one point x_i in the probe and its closest point y_i in the reference. If the distance $d(x_i, y_i)$ is larger than the tolerance D_{max}, p_i equals to 0, which means that x_i and y_i is not a pair of matched point pair. Since ICP is an iteratively adaptive method, for the tolerance D_{max}, it should be updated in every iteration. D_{max}^{I} in iteration I can adapt use the following method.

$$\text{if } \mu < \mathcal{D}, D_{max}^{I} = \mu + 3\sigma$$

$$\text{elseif } \mu < 3\mathcal{D}, D_{max}^{I} = \mu + 2\sigma$$

$$\text{elseif } \mu < 6\mathcal{D}, D_{max}^{I} = \mu + \sigma$$

$$\text{else } D_{max}^{I} = \xi$$

where μ is the mean distance, σ is the deviation of the distances which are given by

$$\mu = \frac{1}{N} \sum_{i=1}^{N} d_i \tag{5}$$

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (d_i - \mu)^2} \tag{6}$$

$\mathcal{D}$ is the threshold controls the quality of the alignment. The value of $\mathcal{D}$ is set by the user. ξ is also a user defined value.

After selecting the matched point pairs, the object function becomes:

$$\mathcal{F}(\mathrm{R},\mathrm{t}) = \frac{1}{N} \sum_{i=1}^{N} \| Rx_i + t - y_i \|^2 \tag{7}$$

where N is the number of matched points between the two data sets (probe and reference).

To minimize the object function (7) the following *lemma* is given to eliminate the translation transformation:

Lemma: Given two 3D point sets: $\{x_i\}_{i=1}^N$ and $\{y_i\}_{i=1}^N$, the function $\mathcal{F}(\mathrm{t}) = \sum_{i=1}^N \|x_i + t - y_i\|^2$ has the minimum when $\mathrm{t} = \frac{1}{N}\sum_{i=1}^N y_i - \frac{1}{N}\sum_{i=1}^N x_i$.[10]

To compute the motion between two 3D data sets (rotation matrix R (3×3) and translation matrix t (3×1)), we use Dual Quaternions method which is proposed by Walker et al. [13] in 1991. Here we just give the brief introduction of Dual Quaternions and the conclusion.

A quaternion **q** is a 4-D vector $[q_1, q_2, q_3, q_4]^T = [\check{q}, q_4]$, where T indicates the transpose of matrix, $\check{q}$ is a 3-D vector which is equal to the values of the original coordinates. q_4 is a scalar, in our experiments, q_4 set to zero. A dual quaternion $\hat{q}$ consists of two quaternions **q** and **s**:

$$\hat{q} = \mathbf{q} + \varepsilon \mathbf{s} \tag{8}$$

Other two 4×4 matrices **Q(q)** and **W(q)** are defined as

$$\mathbf{Q}(\mathbf{q}) = \begin{bmatrix} q_4 I + K(\check{q}) & \check{q} \\ -\check{q}^T & q_4 \end{bmatrix} \tag{9}$$

$$\mathbf{W}(\mathbf{q}) = \begin{bmatrix} q_4 I - K(\check{q}) & \check{q} \\ -\check{q}^T & q_4 \end{bmatrix} \tag{10}$$

Where $K(\check{q})$ is a 3×3 matrix

$$K(\check{q}) = \begin{bmatrix} 0 & -q_3 & q_2 \\ q_3 & 0 & -q_1 \\ -q_2 & q_1 & 0 \end{bmatrix} \tag{11}$$

After given the basic definitions and equations of dual quaternions, the steps of computing the 3D motion are as follows:

Step 1: compute matrices $\boldsymbol{C_1}$ and $\boldsymbol{C_2}$.

$$\boldsymbol{C_1} = -2\sum_{i=1}^N \boldsymbol{Q}(\boldsymbol{y_i})^T \boldsymbol{W}(\boldsymbol{x_i}) \tag{12}$$

$$\boldsymbol{C_2} = -2\sum_{i=1}^N [\boldsymbol{W}(\boldsymbol{x_i}) - \boldsymbol{Q}(\boldsymbol{y_i})] \tag{13}$$

Step 2: compute matrix A.

$$\mathrm{A} = \frac{1}{2}\left[\frac{1}{2N}\boldsymbol{C_2}^T\boldsymbol{C_2} - \boldsymbol{C_1} - \boldsymbol{C_1}^T\right] \tag{14}$$

Step 3: compute the eigenvector **r** corresponding to the largest positive eigenvalue of matrix A, compute **s** from **r**.

$$\mathbf{s} = -\frac{1}{2N}\boldsymbol{C_2}\boldsymbol{r} \tag{15}$$

Step 4: compute rotation R and translation t.

$$\mathrm{R} = (r_4{}^2 - \check{r}^T\check{r})\mathrm{I} + 2\check{r}\check{r}^T + 2r_4K(\check{r}) \tag{16}$$

$$\mathbf{p} = W(\boldsymbol{r})^T\boldsymbol{s} = [\check{p}, p4] \tag{17}$$

$$\mathrm{t} = \frac{1}{N}\sum_{i=1}^N y_i - \frac{1}{N}\sum_{i=1}^N Rx_i \tag{18}$$

Partial ICP is a point-to-point alignment method, the computational cost is large if we use the total points contained in the face images from our database (about 100,000 points). We select to uniform sample our face image before employ partial ICP to reduce the computational cost. Based on the experiments, we decide to select one point between each 10 points in the face images to proceed.

4.2 Scale matrix computation

Partial ICP is an accurate algorithm for rigid data registration and image recognition. But for our face data, scaling effects exist because the distance between the camera and the object is not fixable. We need to consider the scale factor in our face recognition procedure. Du et al. [10] considered the ICP algorithm as a Least Square (LS) problem in order to compute the scale matrix between the two point sets.

The new object function should be:

$$\mathcal{F}(\mathrm{R},\mathrm{S},\mathrm{t}) = \frac{1}{\sum_{i=1}^{m} p_i} \sum_{i=1}^{m} p_i \|RSx_i + t - y_i\|^2 \tag{19}$$

where S is the scale matrix. We only need to consider the matched point pairs, equation (19) becomes:

$$\mathcal{F}(\mathrm{R},\mathrm{S},\mathrm{t}) = \frac{1}{N} \sum_{i=1}^{N} \|RSx_i + t - y_i\|^2 \tag{20}$$

The computation of scale matrix can be concluded as follows:[10]

According to the *lemma*, when $\mathrm{t} = \frac{1}{N}\sum_{i=1}^{N} y_i - \frac{1}{N}\sum_{i=1}^{N} RSx_i$, the object function (20) has the minimum. Hence,

$$\mathcal{F}(\mathrm{R},\mathrm{S}) = \frac{1}{N} \sum_{i=1}^{N} \left\| RS\left(x_i - \frac{1}{N}\sum_{i=1}^{N} x_i\right) - \left(y_i - \frac{1}{N}\sum_{i=1}^{N} y_i\right) \right\|^2 \tag{21}$$

Let $p_i = x_i - \frac{1}{N}\sum_{i=1}^{N} x_i, q_i = y_i - \frac{1}{N}\sum_{i=1}^{N} y_i$, we have

$$\mathcal{F}(\mathrm{R},\mathrm{S}) = \frac{1}{N} \sum_{i=1}^{N} \|RSp_i - q_i\|^2 = \frac{1}{N}\left(\sum_{i=1}^{N} p_i^T S^2 p_i - 2\sum_{i=1}^{N} q_i^T RSp_i + \sum_{i=1}^{N} q_i^T q_i\right) \tag{22}$$

Equation (22) can be treat as a parabola with respect to S. To find out the minimum of this parabola, we can derive the partial differential equation

$$\frac{\partial \mathcal{F}(\mathrm{R},\mathrm{S})}{\partial \mathrm{S}} = 0 \tag{23}$$

In order to get the scale matrix from equation (22), we can get

$$\frac{\partial \mathcal{F}(\mathrm{R},\mathrm{S})}{\partial \mathrm{S}} = 2\sum_{i=1}^{N} p_i^T S E_j p_i - 2\sum_{i=1}^{N} q_i^T R E_j p_i = 0 \tag{24}$$

Where $E_j = diag(0, \ldots, 0,1,0, \ldots, 0), (j = 1,2,3)$ is a diagonal matrix, j-th element is 1 while others are 0.

Scale matrix could be computed from equation (24)

$$S_j = \frac{\sum_{i=1}^{N} q_i^T R E_j p_i}{\sum_{i=1}^{N} p_i^T E_j p_i} \tag{25}$$

In coarse alignment section, we have discussed the boundary a and b of the scale matrix. If $S_j \in [a_j, b_j]$, the minimum is the point which is nearest to the vertex of the parabola (22), the scale can be computed:

$$S_j = \min_{\mathrm{S} \in [a_j, b_j]} \left| s - \frac{\sum_{i=1}^{N} q_i^T R E_j p_i}{\sum_{i=1}^{N} p_i^T E_j p_i} \right| \tag{26}$$

If $S_j < a_j$, $S_j = a_j$, if $S_j > b_j, S_j = b_j$.

The translation can be computed easily:

$$\mathrm{t} = \frac{1}{N}\sum_{i=1}^{N} y_i - \frac{1}{N}\sum_{i=1}^{N} RSx_i \tag{27}$$

The main procedure of our proposed method is:

Input: two 3D point sets $x = \{x_i\}_{i=1}^{N_x}$ and $y = \{y_i\}_{i=1}^{N_y}$.

Output: rotation matrix R (3×3), translation matrix (3×1) and scale matrix (3×3).

Preprocessing:

Step 1: manually select three 7×7 regions as the candidate feature points, and obtain three feature points by curvature analysis.

Step 2: give an initial estimation of the two data sets from three feature points, include rotation matrix R (3×3), translation matrix t (3×1), scale matrix (3×3) and set the boundary of scale matrix.

Iteration begins:

Step 3: find the closest points and discard the unreasonable closest points with the distance constraint D_{max}.

Step 4: compute the scale matrix and motion between two data sets.

Step 5: apply the scale matrix and motion to the model.

Iteration ends if:

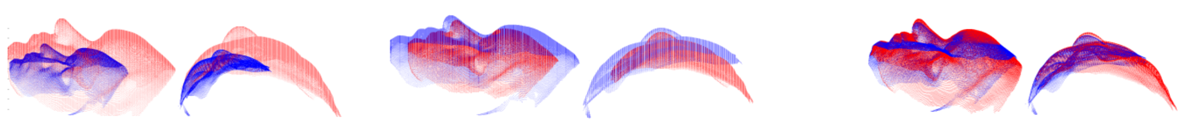
Satisfy the constraint condition for the termination or reach the maximum number of the iteration time. For the terminate condition, we set if $\|R^I - R^{I-1}\| < \varepsilon_R \; and \; \|t^I - t^{I-1}\| < \varepsilon_t \; and \; \|S^I - S^{I-1}\| < \varepsilon_S$, the iteration ends. Where $\varepsilon_R, \varepsilon_t$ and ε_S are three threshold for rotation, translation and scale.

4.3 Matching

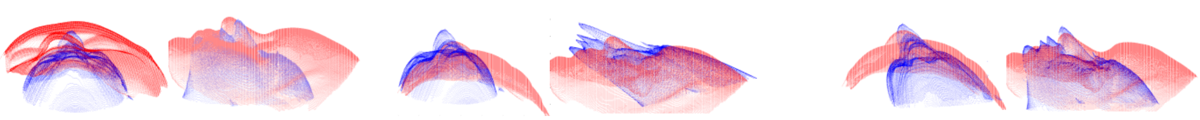
We use the Mean Square Error (MSE) to evaluate the probing image and reference image are from the same person or not. The mean-square function is

$$\mathcal{F}(\mathrm{R}, \mathrm{t}, \mathrm{S}) = \frac{1}{N}\sum_{i=0}^{N}\|RSx_i + t - y_i\|^2 \quad (28)$$

5. EXPERIMENTS



The genuine face images with scale difference.



The different face images.

(a) (b) (c)

Fig. 8. (a) The initial status of two face models. (b) The status after coarse alignment. (c) The final results after fine alignment.

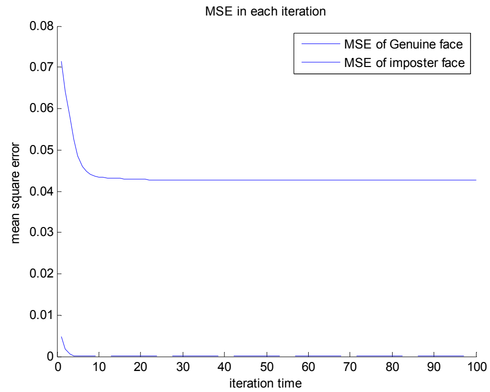
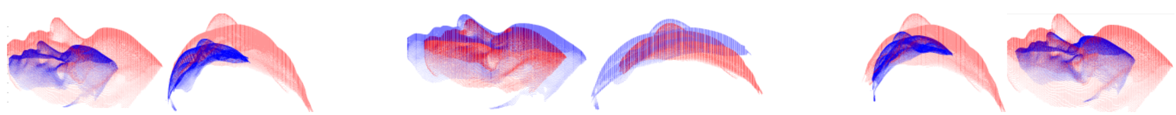
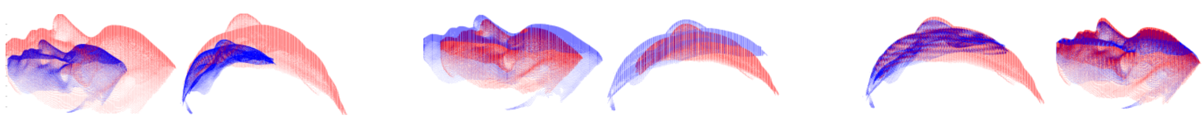


Fig. 9. MSE of the genuine face and imposter face

Fig. 8. shows the experiment results of our proposed method. The top line gives the result when the two face images are the genuine image, while the bottom line is the different face images. The red face image is the reference and the blue one is the probe which has a scale difference compared with the reference. The reference and the probe images in Fig. 8. overlap partially, and the scale factors are different. Column (a) is the initial status of two face images in difference views (x-z view and y-z view). Column (b) is the status of two face images in difference views (x-z view and y-z view) after coarse alignment. Column (c) is the final status of two face images in difference views (x-z view and y-z view). Fig. 9. is MSE results between the genuine image and imposter image. The MSE gives a clear result that the distance difference between the imposter images is much larger than the genuine images. Our proposed method can recognize the same face image and the difference face images, even though the same face images have different rotations and difference scales.



The genuine face images with scale difference applied classic partial ICP.



The genuine face images with scale difference applied partial ICP considered scale.

(a) (b) (c)

Fig. 10. (a) The initial status of two genuine face images with different scales. (b) The status after coarse alignment. (c) The final results after fine alignment.

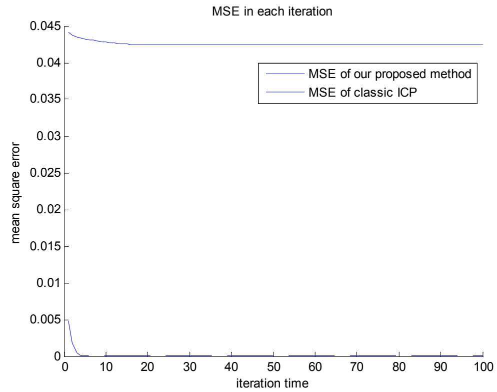
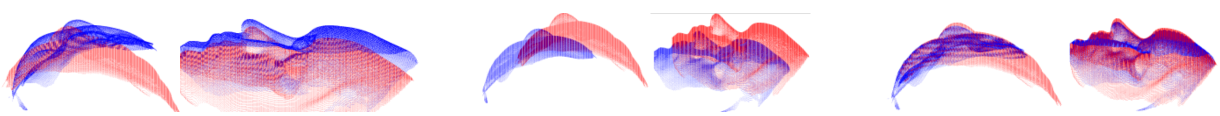
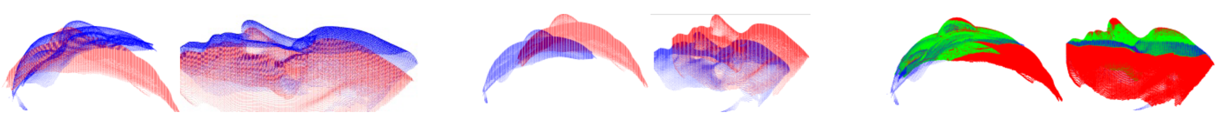


Fig. 11. MSE for ICP considered scale and classic ICP

Fig. 10. gives the comparison results between the classic partial ICP and our proposed method. In Fig. 10., the top line is the genuine face images with scale difference applied classic partial ICP, the bottom line is the genuine face images with scale difference applied our proposed method. From Fig. 10. column (c), we can get that the partial ICP cannot align the two face images with scale difference, while our method can solve the scale difference problem. Fig. 11. is the MSE results compare the classic ICP and our proposed method. From this figure, our proposed method gives a much better result than the classic partial ICP.



The genuine face images without scale difference applied classic partial ICP.



The genuine face images without scale difference applied partial ICP considered scale.

(a) (b) (c)

Fig. 12. (a) The initial status of two genuine face images with the same scale. (b) The status after coarse alignment. (c) The final results after fine alignment.

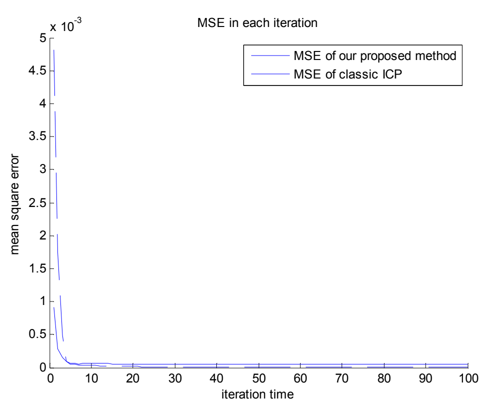


Fig. 13. MSE of our proposed method compared with the classic ICP.

Fig. 12. is the accuracy comparison between the classic partial ICP and our proposed method. In Fig. 12., the two face images in the top line are the genuine face images without scale difference which applied the classic partial ICP, the bottom line is the genuine face images without scale difference which applied our proposed method. From Fig. 13., the MSE between the two methods gives that our proposed method can still keep the similar accuracy with classic partial ICP.

6. CONCLUSION

This paper uses scaling ICP method to deal with the scaling difference problem in partial-matching face recognition. Extracting feature points can give acceptable initial estimation values of scale, rotation and translation for partial-matching problem. Our results show our method can successfully recognize the different face images based on our own database. A small 3D face database built up based on the DFPP data acquisition system which is a simple structure and lower cost 3D data acquisition system.

REFERENCES

[1] Zhao, W., Chellappa, R., Phillips, P. J., and Rosenfeld, A., "Face Recognition: A Literature Survey," ACM Comput. Surv. 35(4), 399-458 (2003).

[2] Bowyer, K. W., Chang, K., and Flynn, P., "A Survey Of Approaches To Three-Dimensional Face Recognition," proc. ICPR 1, 358-361 (2004).

[3] Smeets, D., Claes, P., Vandermeulen, D., and Clement, J. G., "Objective 3D face recognition: Evolution, approaches and challenges," Forensic Sci. Int. 201(1), 125-132 (2010).

[4] Chen, Y. and Medioni, G., "Object Modeling by Reg strat ion of Multiple Range Images," proc. ICRA 3, 2724 - 2729 (1991).

[5] Besl, P. J. and McKay, N. D., "A Method for Registration of 3-D Shapes," IEEE Trans. on Pattern Anal. and Mach. Intell. 14(2), 239-256 (1992).

[6] Zhang, Z., "Iterative Point Matching for Registration of Free-Form Curves and Surfaces," Int. J. Comput. Vision 13(2), 119-152 (1994).

[7] Zha, H., Ikuta, M., and Hasegawa, T., "Registration of Range Images with Different Scanning Resolutions," proc. IEEE ICSMC 2, 1495-1500 (2000).

[8] Zinßer, T., Schmidt, J., and Niemann, H., "Point Set Registration with Integrated Scale Estimation," proc. ICPRIP 116-119 (2005).

[9] Ko, K. H., Maekawa, T., and Patrikalakis, N. M., "Algorithms for Optimal Partial Matching of Free-Form Objects with Scaling Effects," Graph. Models 67(2), 120-148 (2005).

[10] Du, S., Zheng, N., Xiong, L., Ying, S., and Xue, J., "Scaling iterative closest point algorithm for registration of m-D points," J. Vis. Commun. Image R. 21(5-6), 442-452 (2010).

[11] Zhang, S., "Recent progress on real-time 3d shape measurement using digital fringe projection techniques," Opt. Lasers Eng. 48(1), 149-158 (2010).

[12] Dorai, C. and Jain, A. K., "COSMOS-A representation scheme for 3D free-form objects," IEEE Trans. on Pattern Anal. and Mach. Intell. 19(10), 1115-1130 (1997).

[13] Walker, M. W. and Shao, L., "Estimating 3-D Location Parameters Using Dual Number Quaternions," CVGIP-Imag. Understan. 54(3), 358-367 (1991).