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LETTER

3D Face Recognition Based on MPU Implicits

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SUMMARY In this paper, we present an approach for 3D face recognition based on Multi-level Partition of Unity (MPU) Implicits under pose and expression variations. The MPU Implicits are used for reconstructing 3D face surface in a hierarchical way. Three landmarks, nose, left eyehole and right eyehole, can be automatically detected with the analysis of curvature features at lower levels of reconstruted face. Thus, the 3D faces are initially registered to a common coordinate system based on the three landmarks. A variant of Iterative Closest Point (ICP) algorithm is proposed for matching the point surface of a given probe face to the implicits face surface in the gallery. To evaluate the performance of our approach for 3D face recognition, we perform an experiment on GavabDB face database. The results of the experiment show that our method based on MPU Implicits and Adaptive ICP has great capability for 3D face recognition under pose and expression variations.
key words: *3D face recognition, MPU Implicits, Adaptive ICP*

1. Introduction

Face recognition has been one of the most active research areas in pattern recognition and computer vision. Most of the studies have focused on 2D intensity image, but the performance of 2D face recognition [1] still suffers from pose and illumination variations. As a robust face recognition system to overcome these limitations, 3D face recognition [2] is attracting attention. But there still exist some difficulties in 3D face recognition, such as expression variations and large computational costs. In this paper, we present an approach for 3D face recognition based on Multi-level Partition of Unity (MPU) Implicits [3] under pose and expression variations. The idea of using MPU Implicits in a hierarchical way is proposed for reconstruction of face surface. Landmarks are automatically extracted from lower levels of reconstructed faces. The 3D faces are initially registered to a common coordinate system based on the landmarks. We extract expression insensitive regions of the face and use Adaptive ICP, a variant of ICP [4] algorithm, for matching. Adaptive ICP avoids the most time consuming process of ICP. This proposed method is invariant to holes and noise. The experimental results using GavabDB database [5] show the great performance for 3D face recognition.

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2. 3D Recognition Based on MPU Implicits

2.1 MPU Implicits

The multi-level partition of unity implicits surface (MPU) [3] allows us to construct surface models from very large sets of points. There are three key ingredients to MPU: 1) piecewise quadratic functions that capture the local shape of the surface, 2) weighting functions (the partitions of unity) that blend together these local shape functions, and 3) an octree subdivision method that adapts to variations in the complexity of the local shape.

For a bounded domain Ω in a Euclidean space, given a set of nonnegative compactly supported functions $\{w_i(x)\}$, an approximation of a function $f(x)$ defined on Ω is given by:

$$f(x) = \frac{\sum w_i(x) Q_i(x)}{\sum w_i(x)} \tag{1}$$

where, Q_i is the local approximation set of functions with each subdomain.

For approximation purposes we use the quadratic B-spline $b(t)$ to generate weight functions

$$w_i(x) = b(\frac{3|x - c_i|}{2R_i}) \tag{2}$$

Given a set of scattered points P equipped with normals N, we approximate the signed distance function $f(x)$ from P.

$$w_i(x) = \left[\frac{(R_i - |x - c_i|)_+}{R_i|x - c_i|}\right]^2 \tag{3}$$

where $(a)_+ = \begin{cases} a & if\ a > 0 \\ 0 & otherwise \end{cases}$, c_i is the center of a cubic cell that was generated during the subdivision process, and R_i is a spherical support of radius.

First, we use an octree-based adaptive space subdivision of Ω to control the error of the approximation while adapting the complexity of the representation to the complexity of the shape.

Second, we use piecewise quadratic functions resulting from Boolean operations for the accurate representation of sharp features. One of three local approximations is used:

(a) A general 3D quadric, which is used to approximate larger parts of the surface. A local shape function is given

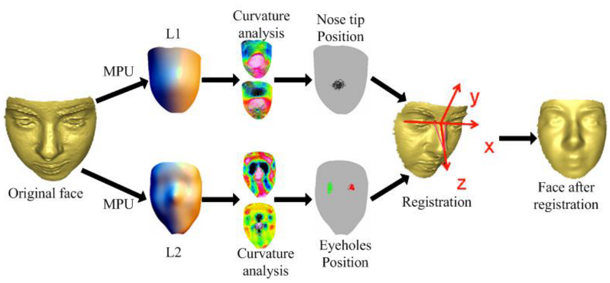

Fig. 1 Processing steps of face registration.

by:

$$Q(x) = x^T A x + b^T x + c \tag{4}$$

(b) A bivariate quadratic polynomial in local coordinates, which is used to approximate larger parts of the surface. A local shape function is given by:

$$Q(x) = w - (Au^2 + 2Buv + Cv^2 + Du + Ev + F) \tag{5}$$

(c) A piecewise quadric surface that fits an edge or a corner. For the surface P with an edge, we subdivide P into two clusters P_1 and P_2 according to normals. The quadratic fit procedure is applied separately to P_1 and P_2 and a non-smooth local shape function approximate P is constructed via the max/min Boolean operations. For the surface N with a corner, we subdivide N into three sets, N_1 and N_2 are constructed as above. For the corners of degree four, the third cluster is subdivided into two pieces. If the resulting four clusters of normals correspond to either a convex or concave corner, it is reconstructed via Boolean operations. Otherwise, we go to (a) and a general quadric is fitted to P. More complex types of sharp features are approximated by smooth functions.

2.2 Landmarks Detection and Initial Registration

The MPU Implicits [3] are used for reconstructing face surface in a hierarchical way. Once the different levels are acquired, surface curvature, which has the valuable characteristic of being viewpoint invariant, is exploited respectively to the second level (L1) and the third level (L2) to segment the eyeholes and nose regions. An mean and Gaussian (HK) classification [6], based on the signs of mean and Gaussian curvature, divided the face into six types: hyperbolic, Convex cylindrical, Convex elliptical, Planar, Concave cylindrical and Concave elliptical. The nose region can be found in L1, which is elliptical convex and the eyehole regions are found from the high negative mean curvature and high Gaussian curvature in L2. Experimental results show that this method is accurate. For more details, see [9]. The three landmarks are used as a reference to register the face surfaces. Figure 1 presents a description of the processing steps. Accurate registration can reduce the timing-consuming during face matching.

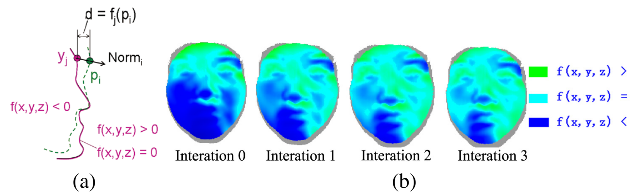

Fig. 2 (a) Finding the responding point of Adaptive ICP. (b) Result of Adaptive ICP.

2.3 Face Matching Based on Adaptive ICP

The gallery faces are reconstructed by MPU Implicits as implicit models and the probe faces are point set models. We propose a variant of ICP [4] method, namely Adaptive ICP, to finely register a point set model with an implicit model. Instead of using the nearest point as the responding point, we use the intersection of normal and the implicit model as the responding point. As show in Fig. 2 (a), the reference data is a set of implicits $F = \{f_j\}$ and the test data is a set of points $P = \{p_i\}$. For each point p_i, $Norm_i$ is the norm of p_i.

The intersection of $Norm_i$ and F is y_j, y_j is the responding point of p_i:

$$y_j = p_i - f_j(p_i) * Norm_i \tag{6}$$

The distance between y_i and p_i is:

$$d = f_j(p_i) \tag{7}$$

ICP algorithm time complexity is $O(N_p N_q)$ and the time complexity of K-D Tree acceleration method is $O(N_p log N_q)$. By using the MPU implicits models as gallery face models, Adaptive ICP avoid the process of searching the closest point, which reduces the time complexity to $O(N_p)$. Figure 2 (b) shows the result of Adaptive ICP.

3. Experiment Results

The experiment has been performed using models from the GavabDB database [5]. This database includes 3D facial surfaces of 61 individuals (45 males and 16 females). Each image is given by a mesh of connected 3D points of the facial surface in the VRML format without texture. Due to errors in the acquisition steps, some of the faces contain significant amount of noise or holes on the face. Some artifacts such as hair, beard and moustache are also presented. In our experiments, we used the two neutral models, the two neutral looking up and down models, the frontal models with smile expression, and the frontal models with random gesture. The models in the second capture are used as gallery models and other models are used as the probe models for recognition.

In the offline process, the gallery faces are initially registered by the method proposed in Sect. 2.2 and then reconstructed by MPU implicits. In the online process, the probe models are initially registered, to weaken the effects of expression, only the upper part of the face (i.e., face surface around the eyes and the nose) are considered. We use Adaptive ICP algorithm to finely register a 3D probe face surface with a given 3D gallery face surface and compute the MSE (mean square error) [4] between the two surface. Figure 3 is the flow chart of face matching.

Table 1 lists the results of the experiments. For neutral frontal models, the rank-one recognition rate is 94.83%. We evaluate the performance of our method for recognition of facial models with pose (looking up/down). As a result, the recognition rates for facial models with looking up (down) pose are 89.93% and 89.66%. Furthermore, we consider the facial models with expression. We achieve a recognition rate of 91.83% for the smiling expression and 81.82% for the random gesture.

We compare our method with different approaches that are presented by M. Mahoor [7] and A. Moreno [8] based upon the GavabDB database in Table 1. As the results show, our method has a similar performance as M. Mahoor's ICP method [7] with neutral models. Furthermore, our method has a better recognition performance with poses and with expressions. The experiment results show that the 3D face recognition method based on MPU Implicits and Adaptive ICP has a better recognition performance for faces with expression and with poses.

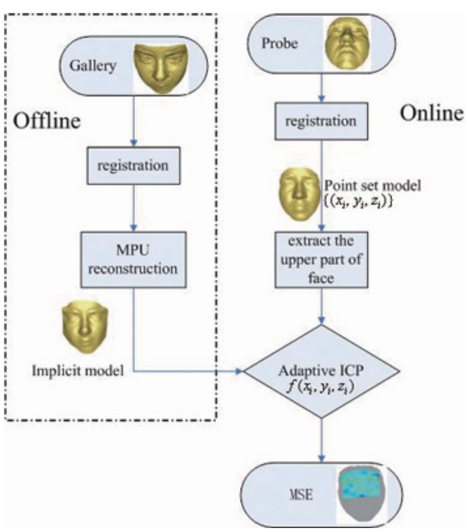

Fig. 3 Flow chart of face matching.

Table 1 Our experiment results comparing the results by M. Mahoor [7] and A. Moreno [8] based upon the GavabDB database.

	Our method	M. Mahoor [7]		A. Moreno [8]
		Robust HD	ICP	
Neutral	94.83	93.5	95	90.16
Looking up	89.93	75.4	88.6	
Looking down	89.66	70.5	85.3	
Smiling	91.83	82	83.6	77.9
Random gesture	81.82	63.4	63.4	

Furthermore, we compare the computation time of our method to ICP using K-D Tree. The average computation time of matching one face model is 3.20 seconds by using MPU implicits and Adaptive ICP. The method of ICP using K-D Tree needs 4.84 seconds. Experimental results show that our method reduces the computational costs and saves timing-consuming.

4. Conclusion

This paper presents a method for 3D face recognition using MPU Implicits based on 3D faces. 3D faces are reconstructed by MPU Implicits in a hierarchical way. Curvature analysis is carried out on different levels of reconstructed facial surfaces. Candidate regions, including nose and eyeholes, are isolated using mean and Gaussian curvature features maps that highlight the curvature properties. The 3D faces are initially registered according to the three landmarks and then finely registered by Adaptive ICP. Only the upper part of the face (i.e., face surface around the eyes and the nose) are considered for matching. Experimental results on the GavabDB show that our method has great capability for 3D face recognition under pose and expression variations.

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