AUTOMATIC 3D FACE VERIFICATION FROM RANGE DATA

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ABSTRACT

In this paper, we presented a novel approach for automatic 3D face verification from range data. The method consists of range data registration and comparison. There are two steps in registration procedure: the coarse step conducting the normalization by exploiting *a priori* knowledge of the human face and facial features, and the fine step aligning the input data with the model stored in the database by the partial directed Hausdorff distance. To speed up the registration, a simplified version of the model is generated for each model in the model database. During the face comparison, the partial Hausdorff distance is employed as the similarity metric. The experiments are carried out on a database with 30 individuals, and the best EER of 3.24% is achieved.

1. INTRODUCTION

The automatic face recognition based on 2D image processing has been actively researched in recent years, and various techniques have been presented. Although great strides have been made during the past three decades, the task of robust face recognition is still difficult. Current methods work very well under conditions similar to those of the training images. However, either of the illumination variation and pose change may cause serious performance degradation for most existing systems.

The 3D data have the potential to overcome these problems, whose advantage is the explicit representation of 3D shape. Recent advances in modelling and digitizing techniques have made the construction of 3D human face models much easier [1]. But the activities to exploit the additional information in 3D data to improve the accuracy and robustness of face recognition system are still weakly addressed. Only a few works on the use of 3D data have been reported. Several studies concentrated on curvature analysis. Gordon [2, 3] presented a template-based recognition system involving descriptors based on curvature calculations from range image data. The sensed surface regions are classified as convex, concave and saddle by calculating the minimum and maximum normal curvatures. Then locations of nose, eyes, mouth and other features are determined, which are used for depth template comparison. Lee et al [4] proposed a method to detect corresponding regions in two range images by graph matching based on extended Gaussian image. An approach to label the components of human faces is proposed by Yacoob et al [5]. Its preprocessing stage employs a multistage diffusion process to identify convexity and concavity points. These points are grouped into components. Qualitative reasoning about possible interpretations of the components is performed, followed by consistency of hypothesized interpretations. However, because they are involved in computing curvatures, either of these techniques requires high quality of the range data, otherwise the computation of curvature will be inaccurate and unreliable. Chua et al [6] describes a technique based on point signature - a representation for free-form surfaces. The rigid parts of the face of one person are extracted to deal with different facial expressions. Beumier et al [7] proposed two 3D comparison methods respectively based on surface matching and profiles matching. Recently Blanz [8] utilized a 3D morphable model to tackle variation of pose and illumination in recognition from facial images, however, the matching procedure is hugely time-consuming of 40 minutes on Pentium III, 800MHz.

In this paper, a novel method for full automatic 3D face verification from range data is presented. It can work well with a low-resolution 3D facial data (only nearly 3000 points) and can compare two models in several seconds. The experimental results on $3D\_RMA$ database (part of M2VTS project) are reported.

2. FACIAL DATA REGISTRATION

A object recognition system generally makes up of two key parts: data registration and data comparison. The accuracy of registration will greatly impact on the result of following comparison. Although Blanz[9] gave a nice solution to registration of 3D facial data, high time-cost made it hard to be incorporated into a practical recognition system. Here we propose a coarse-to-fine registration scheme. It works well on the range data from $3D\_RMA$.

Given two sets of facial range data $S = \{s_1, \cdots, s_k\}$ and $M = \{m_1, \cdots, m_n\}$, the task of 3D registration is to find the transformation (translation, rotation and scaling) which will optimally align the regions of S with those of M. For a transformation group G, it can be formalized as an optimization problem:

$$\min_{g \in G} \delta(M, g(S)) \tag{1}$$

In other words, we should find a certain transformation $g \in G$ which matches M with $g(S)$ as "$closely$" as possible in terms of closeness evaluation function $\delta(.)$.

To speedup the registration process and improve the performance, the registration process consists of the coarse normalization and the fine alignment. In the coarse step, a priori knowledge of the human face and facial features is exploited. After the coarse normalization, the directed version of partial Hausdorff distance [10] is employed as the closeness evaluation function to refine the registration.

2.1. Coarse normalization

Assume that the given range data represent a human face. Therefore the knowledge involving the face and facial features can be exploited. Firstly, the face-surface may be approximately regarded as a plane, considering computational simplicity of the plane, although the ellipsoidal surface is preferred. Secondly, the prominence of the nose can be localized easily and robustly. However, for $3D\_RMA$, detection of mouths and eyes may be difficult and disturbed due to the limited quality of the range data.

Thus, for a facial model or point set S, the coarse normalization is achieved by:

1. Fit a plane to S, shown in Fig. 1.
2. Detect frontal view and back view on the basis of point distribution on both sides of the plane.
3. Find the location of nose tip.
4. Approximately detect the chin and cheeks and estimate the width and height of face by the location of chin and cheek.
5. Translate, rotate and scale S according to the parameters obtained from 1-4.

2.2. Fine alignment

In the fine step, we choose the directed version of partial Hausdorff distance as the closeness evaluation function $\delta(.)$ but not the partial Hausdorff distance, since the former has similar performance with the latter but less computational cost.

The Hausdorff distance is a metric between two finite point sets, which has been successfully applied to computer vision and computational molecular biology. It is insensitive to small perturbations of the point sets, and allows for small positional errors in point sets.

Given two finite point sets $A = \{a_1, \cdots, a_m\}$ and $B = \{b_1, \cdots, b_n\}$, the *partial directed Hausdorff distance* from A to B is defined as

$$h_L(A, B) = L^{th}_{a \in A} \min_{b \in B} \rho(a, b) \tag{2}$$

Where $\rho(a, b)$ is a distance metric. In this paper, L_1 metric is employed for less latency time. The *partial (undirected) Hausdorff distance* between A and B is then defined as

$$H_{LK}(A, B) = \max(h_L(A, B), h_K(B, A)) \tag{3}$$

The user specifies the fraction f_1 and f_2, $0 \leq f_1, f_2 \leq 1$, which determine $L = \lfloor f_2 m \rfloor$ and $K = \lfloor f_1 n \rfloor$. Thus, the optimization problem of the fine alignment becomes:

$$\min_{g \in G} h_L(M, g(S)) \tag{4}$$

There are several approaches to solve this optimization problem to find the optimal transformation in the seven-dimension space (three for translation, three for rotation and one for scaling)., such as Powell method.

3. 3D FACE VERIFICATION

3.1. The model database

Prior to the online recognition, the model database must be built up. In our approach, only one 3D facial model (point set) is required for each person. If cardinality of two point sets is m and n respectively, the computation of the Hausdorff distance will take time $O(mn)$. To speedup alignment process, a simplified version of the model is produced off-line semi-automatically, whose cardinality is often less than one-fifth of cardinality of the original model. It keeps some significant points for registration. Thus, the simplified model acts as the stand-in of the original model during the fine alignment step. Consequently, for each person, there are two version of its model in the model database. One is the original model that has been normalized; the other is the simplified version of the original model.

3.2. 3D model comparison

The similarity measure between two 3D face models is defined as the partial Hausdorff distance in Equ. 3, in view of its robustness and efficiency.

For the model M from the model database and the model S from the input, the procedure of comparison is described below:

1. Perform the coarse normalization on S.
2. Align S with model M', which is the simplified version of the model M, to find the transformation g_0 which minimizes $h_L(M', g(S))$.
3. Get the similarity between S and M by calculating $H_{LK}(M, g_0(S))$.

4. EXPERIMENTAL RESULTS

Our experiments use the facial range data from $3D\_RMA$ database, which is a part of M2VTS project. The range data were obtained by a 3D acquisition system based on structured light, in xyz form. There are about 3000 points in a model. It consists of four parts ($DBs1m, DBs2m, DBs1a, DBs2a$) that were build up from two sessions taken in different time separated by several months. See [7] for more details. In each part a person has exactly three shots with different orientation of head: straight forward, left or right, upward or downward, and some people smiled in some shots. Since spectacles, beards and moustaches may be present, some facial features are often incomplete, like nose, eye. Figure 2 shows two examples, two views for each.

The proposed approach is implemented on the Pentium IV 1.5GHz. Two parameters f_1 and f_2 of the partial Hausdorff distance are always set to the same, denoted by f . It takes about 5 seconds to compare two 3D face models, including registration and calculation of similarity.

Verification results on three databases are shown in 3^{th} column of Table 1. For tests on $DBs1m$ and $DBs2m$, the model database is made up of the first shot of each person (30 models totally), and the remains of the session (two shot) act as the probe data. For tests on $DBs1m$+$s2m$, the model database consists of the first shot of $DBs1m$, all shots in $DBs2m$ and the remains of $DBs1m$ act as the probe data. ROC curve shown in Fig. 4. The best EER performance, achieved for $DBs1m$, reaches 3.24%.

We also implemented the verification approach based on eigenspace, which is composed of three consecutive parts: the proposed facial data registration, conversion of 3D data into 2D facial range image based on triangle-based linear interpolation, and verification in the facial image eigenspace like [11]. EER by it is shown in 2^{rd} column of Table 1. Although it is outperformed by the approach with similarity metrics of Hausdorff distance, its performance is similar to the one by [7].

The experiment on $DBs1m$ for the effect of the fraction parameter in the partial Hausdorff distance is carried out. The result of EER is shown in Fig. 3. It is obvious that the best rate is achieved around 0.8.

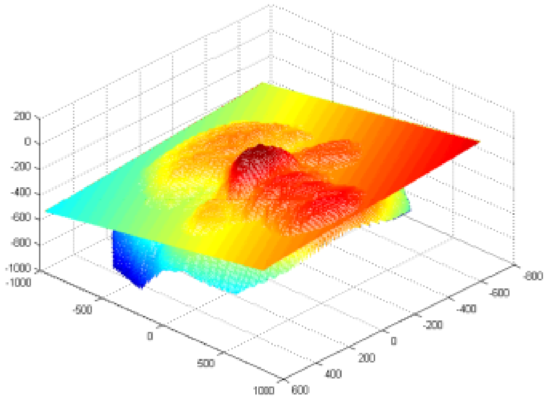

Fig. 1. Fit a plane to a 3D face model.

5. CONCLUSIONS

A novel approach for full automatic 3D face verification from range data is presented, which consists of facial range data registration and comparison. The coarse-to-fine registration includes: the coarse step conducting the normalization by exploiting a priori knowledge of the human face and facial features, and the fine step aligning the input data with the model. During the facial model comparison, the partial Hausdorff distance is engaged. The experiments on the $3D\_RMA$ database show that the proposed approach can work well with the low-resolution of facial range data, and also can deal with variation of pose and some changes of expression.

6. ACKNOWLEDGMENTS

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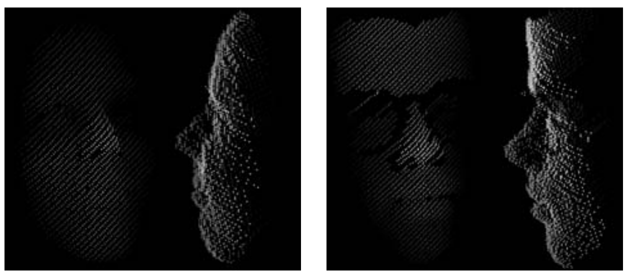

Fig. 2. Two sample models from $3D\_RMA$, two views for each model.

Databases	Eigenspace	Hausdorff
$DBs1m$	5.0%	3.24%
$DBs2m$	6.67%	5.0%
$DBs1m$+$s2m$	7.33%	5.33%

Table 1. EER on three databases, each database has 30 individuals.

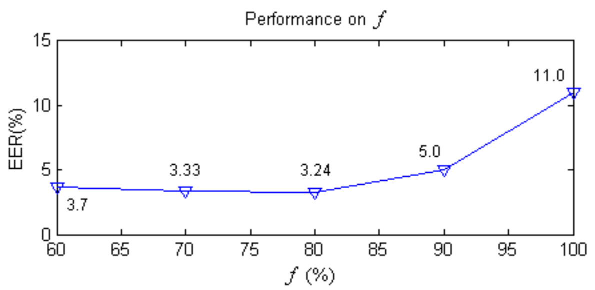

Fig. 3. EER on $DBs1m$ with different fraction in the partial Hausdorff distance.

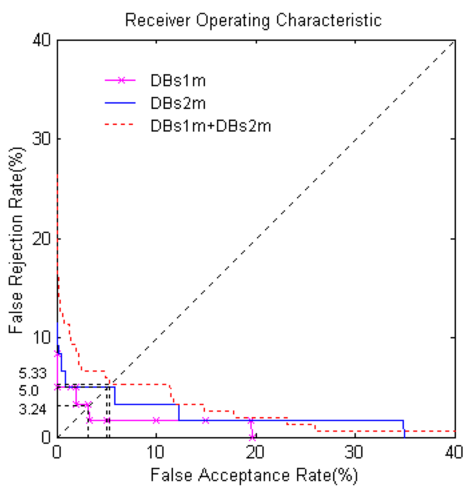

Fig. 4. ROC curves (30 persons and f=0.8).

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