A Novel 3D Face Recognition Algorithm Using Template Based Registration Strategy and Artificial Neural Networks

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Abstract. In this paper, we present a novel algorithm for 3D face recognition that is robust to the rotations and translations of the face models. Based on the Iterative Closest Point algorithm, a template based registration strategy is proposed for data normalization. Back-Propagation neural networks are then constructed to perform recognition tasks. The proposed algorithm is general purpose and can be applied for common 3D object recognitions. Experimental results illustrate that the algorithm is effective and robust.

1 Introduction

A 3D face model, or a point cloud, is a depth image consisting of a set of 3D points generated from laser scanners or structured lights. The images are usually captured from different viewpoints and distances. Each of them has its own local coordinate system. In order to use the 3D data for building recognition systems it is necessary to transform them into a common coordinate system. This procedure is usually referred to as registration, or normalization. After data normalization, similarity measures are developed for face matching and recognition.

Various approaches have been proposed for 3D point cloud registration and matching. Moreno and Sanchez [1] compute the Gaussian and the mean curvatures of the surface to extract feature points for local coordinate construction and alignments. Euclidean distances among the feature vectors are used for similarity measurement. Zhang *et al* [2] apply Principal Component Analysis to roughly obtain the medial axis of the face model and then use ICP algorithm to refine the registration. The matching process is also based on the Euclidean distance. Lu *et al* [3] use ICP algorithm directly for both face alignment and face matching. The similarity measure is the ICP distance error between the data and the template models.

2 Iterative Closest Point Algorithm

The iterative closest point (ICP) algorithm proposed by Besl and McKay [4] is a widely used method for 3D point cloud registration. The basic ICP algorithm is described as:

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Given a template model X and a data model P find the optimal rotation matrix and the translation matrix that minimize the distance error between X and P.

Algorithm. Iterative Closest Point

Step 1. $\forall p \in P$ find its closest point $x \in X$

Step 2. Find transformation Q to minimize the distances between each p and x

Step 3. $P_{k+1} \leftarrow Q(P_k)$

Step 4. Repeat the above steps until the distance error reduce to a minimal level.

3 Registration

We develop a template based strategy to normalize 3D point clouds for neural network training. A face model is selected as the standard coordinate template. All the other face models in the database are aligned to it. The algorithm makes use of the ICP algorithm. Other optional surface alignment algorithms such as the Least-square-based surface matching [6] proposed by Gruen and Akca can also be applied. The complexity of the ICP algorithm employed is $O(N_p N_x)$, where N_p and N_x are the number of points in the data model and template, respectively. In the experiment, to reduce the complexity we also coarsen the 3D point clouds uniformly before aligning them to the standard template. The ultimate transformation matrixes for 3D rotations and translations can be obtained by combining a series of intermediate transformation matrixes generated in the alignment iterations. Let there be n iterations to transform from P_0 to X where X and P_0 are the template and the original data models. Denote R_i and T_i as the rotation and the translation matrixes corresponding to the i^{th} ICP iteration. P_i is the transformed image from P_{i-1} using R_i and T_i. Therefore,

$$P_1 = R_1 \cdot P_0 + T_1,\ P_2 = R_2 \cdot P_1 + T_2,\ \ldots,\ P_i = R_i \cdot P_{i-1} + T_i,\ \ldots,\ X = R_n \cdot P_{n-1} + T_n .$$

Combine them together, we get.

$$X = \left(\prod_{i=1}^{n} R_i\right) \cdot P_0 + \left[\sum_{j=2}^{n}\left(\prod_{i=j}^{n} R_i\right) \cdot T_{j-1} + T_n\right]. \tag{1}$$

The ultimate transformation matrixes for rotation and translation are denoted as,

$$R = \prod_{i=1}^{n} R_i \ . \tag{2}$$

$$T = \sum_{j=2}^{n}\left(\prod_{i=j}^{n} R_i\right) \cdot T_{j-1} + T_n \ . \tag{3}$$

The transformations R and T are then applied back to the full scale point set for registration.

4 Experiment

The 3D face data set [1] we are working on contains 427 three dimensional facial surface images corresponding to 61 individuals (45 male and 16 female). Using the neural networks for classification the Maximum accuracy rate achieved for distinguishing a subset of faces is 100%.

5 Conclusion

In this paper, we have presented a novel algorithm for 3D face recognition. A template based registration strategy is proposed for data normalization. Back-Propagation neural networks are trained for face matching and retrieval. Experimental results show that the algorithm is invariant to rotations, translations, illuminations. It is also robust to the incomplete and ill-formed 3D point cloud data. The template based registration strategy and the neural network approach for face similarity measurement can be generalized for common 3D object recognitions.

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