A Genetic Algorithm Based Feature Selection Approach for 3D Face Recognition

Yi Sun and Lijun Yin
State University of New York at Binghamton, Binghamton, New York 13902
{*ysun, lijun*}*@cs.binghamton.edu*

1. Introduction

Research on 3D face recognition [1,9] has been intensified recently due to the significant advances of the 3D imaging technology. Most of the research focuses on the investigation of 3D range data obtained by a 3D scanner. Although 3D capture systems provide highly accurate 3D face information, it is not trivial to process the large amount of facial surface data. For example, it is hard to keep the correspondences among different subjects because their models have different vertices, and a post-processing procedure needs to follow because the range data may contain too much redundant information, which may make the facial shape comparison noise sensitive. In this paper, we propose to use a generic model to construct the 3D facial feature space. Figure 1 shows the scheme of our proposed method. This approach relies on our realistic face modeling technique, by which the individual face model is created using a generic model and two views of a face. The feature space is composed of geometrical structures, the labeled curvature types of each vertex in the individualized model. Some research used statistics approaches, such as PCA, ICA and LDA [11], to form a feature space. Since they mainly rely on feature transformation procedures, which project the original feature set into a more compact set while retain the necessary information, some features that confuse the recognition task may still be chosen. In our approach, the optimized features are selected by using a Genetic Algorithm based approach. This feature selection approach maintains the "good" features that minimizes the inner-class distance and maximizes the intra-class distance. We tested on two sets of databases. One set consists of 105 3D facial models, about 92% rank-four correct recognition rate is achieved. The other set has 387 models, the correct recognition rate is 87.6%. The experimental results show that the features obtained from the 3D individualized model is feasible to classify and identify individual faces.

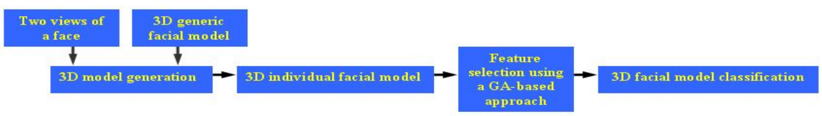


Figure 1: The scheme of proposed 3D face recognition system

2. Feature space construction and selection using a GA-based approach

Based on our existing work [2], we created a 3D facial model database by modifying a generic facial model to customize each individual face, given a front view and a side view of one face. This approach is based on recovering the structure of selected feature points in the face and then adjusting a generic model using these control points to obtain the individualized 3D facial model. Each individualized facial model consists of 2953 vertices. Our 3D face model database is generated using 105 pairs of face images from 40 subjects. These source image pairs are mainly chosen from the databases of [3,4], and some additional images are captured from our local community. For each subject, there are two or three pairs of frontal and profile images, which were taken under different imaging conditions. In order to better characterize 3D features of the facial surface, each vertex on the individual model is labeled by one of eight label types [6]. Therefore, the facial feature space is represented by a set of labels. A cubic approximation methods [5] is explored to estimate the principal curvatures of each vertex on the model. Then the eight typical curvature types (i.e., convex peak, convex cylinder/cone, convex saddle, minimal surface, concave saddle, concave cylinder/cone, concave pit and planar) are categorized according to the relation of the principal curvatures [6]. Figure 2(a) shows the labeled original feature space. Among the set of labels, only the labels located in certain regions are of our most interest. Some non-feature labels could be noises that may blur the individual facial characteristics. Therefore, we need to apply a feature screening process to select features in order to better represent the individual facial traits for maximizing the difference between different subjects while minimizing the size of the feature space. In order to select the optimal features, we partition the face model into 15 sub-regions based on their physical structures(there are overlaps between some of the regions), which is similar to the region components used in [8], as expounded in Figure 2(b). Since not all the sub-regions contribute to the recognition task, and not all the vertices within one sub-region contribute to the classification, we need to select the best set of vertex labels and the best set of sub-regions. The purpose of the feature selection is to remove the irrelevant or redundant features which may degrade the performance of face classification. The genetic algorithms (GA) is

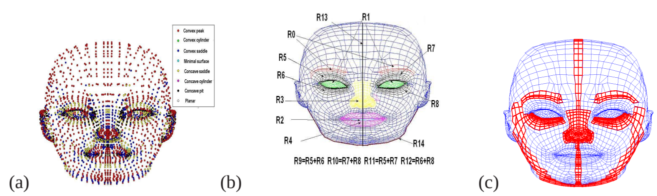
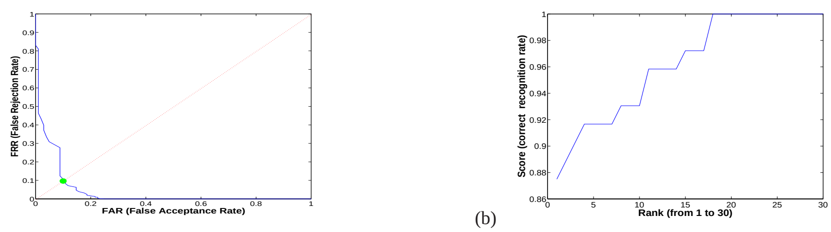


Figure 2: (a) Labeled feature space. (b) Sub-regions. (c) Optimal feature space.

used successfully to address this type of problem [10]. So we choose to use a GA-based method to select the components that contribute the most to our face recognition task. The procedure for the GA-based feature selection consists of two parts: (1) vertices selection in each sub-region and (2) the integration of sub-regions. In the first stage, equal error rate (EER) is used as the fitness function and those resulting in a higher EER rate are selected as good features. In the second stage, the sub-regions whose EER rate are higher than the mean EER rate value are integrated together as the final optimal feature spaces. Figure 2(c) shows the optimized feature space that marked with red color.

3. Experimental results

In the first 3D face model database, there are 40 subjects with total 105 instance models (note that each subject has two or three generated instance models depending on two or three pairs of instance images available.) Since the size of our database is not large enough, we chose the 10-fold cross validation [7] method to do the feature selection. So for each time, we randomly selected 10 models as the validation set and the left as the training set. Using the method described in Section 2, 137 feature vertices are finally included in the optimal feature space. We chose the correlation to measure the similarity of two feature vectors. The high correlation value of two feature vectors implies the high similarity of the two individual models. As a result, the individual models can be simply classified according to their correlation values. The test is performed on the whole 105 models. The performance of the 3D facial model classification is illustrated by a ROC curve, as shown in Figure 2(a), and the EER rate is 9%. Figure 2(b) shows the correct recognition rates using the score vs. rank curve. Our approach achieves a 92% correct recognition rate if the first four candidates (rank=4) are selected. We also tested on the second set of model database, which contains 387 models captured from the external community with various lighting and pose conditions. We used the same 137 feature vectors to test these 387 models and achieved about 87.6% rank-four recognition rate. This shows the good applicability of our generated optimal feature space.



(a) (b)

Figure 3: (a) ROC curve and (b) Accumulative score vs. rank

4. Conclusions and future work

We proposed a curvature-based feature space construction and a GA-based feature selection scheme for 3D face recognition, which performs well for characterizing the individuals' 3D features. More work is to be done to expand the existing database to a large scale and to conduct the intensive test for the data obtained under variable imaging conditions. Since our reconstructed model is a rough representation of a facial surface, we will do the comparative recognition test between our model and the 3D range data to demonstrate the robustness and accuracy of our method. In the future, we will also consider to design a better feature selection algorithm that incorporates multiple feature descriptors combined with normal maps, curvature maps and label maps, and to use a multi-classifier strategy to enhance the system performance.

5. Acknowledgment

This material is based upon work supported by the National Science Foundation under Grant No. IIS-0414029.

References

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

[2] H. Ip, and L. Yin. "Constructing a 3D Individualized Head Model from Two Orthogonal Views," *The Visual Computer*, 12, Springer-Verlag, pp 254-266. 1996

[3] The FERET Database. `http://www.itl.nist.gov/iad/humanid/feret/feret_master.html`.

[4] The XM2VTS Database. `http://www.ee.surrey.sc.uk/Research/VSSP/xm22vtsdb/`.

[5] J. Goldfeather and V. Interrante, "A Novel Cubic-Order Algorithm for Approximating Principal Direction Vectors.", *ACM Transactions on Graphics*, Vol. 23, No. 1, January 2004, pp. 45-63.

[6] H. Tanaka, M. Ikeda and H. Chiaki, "Curvature-based face surface recognition using spherical correlation," *IEEE International Conference on Face and Gesture Recognition*, pp. 372-377, 1998.

[7] R. Kohavi, "A study of cross-validation and bootstrap for accuracy estimation and model selection," *In Proceedings of the Fourteenth International Joint Conference on Artificial Intelligence*, pp. 1137-1143, 1995.

[8] J. Huang, V. Blanz, and B. Heisele. "Face Recognition with Support Vector Machines and 3D Head Models," *International Workshop on Pattern Recognition with Support Vector Machines (SVM2002)*, Niagara Falls, Canada, p334-341, 2002.

[9] P. J. Phillips, P. J. Flynn, T. Scruggs, K. W. Bowyer, J. Chang, K. Hoffman, J. Marques, J. Min, and W. Worek, "Overview of the Face Recognition Grand Challenge," *In Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, 2005.

[10] G.Van Dijck, M.M. Van Hulle, and M. Wevers, "Genetic Algorithm for Feature Subset Selection with Exploitation of Feature Correlations from Continuous Wavelet Transform: a real-case Application," *International Journal of Computational Intelligence*, 1(1) 2004,pp. 1-12.

[11] X. Liu, A. Srivastava, and K. Gallivan, "Optimal Linear Representation of Images for Object Recognition," *IEEE Trans. Pattern Anal. Machine Intell.* Vol. 26, no. 5, pp. 662-666,2004.