3D Face Recognition Using Range Images

Final Report

Multidimensional DSP

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Abstract

In this project, a new face recognition algorithm based on range images of human faces will be presented. Range images have several advantages over 2D intensity images and 3D meshes. Range images are robust to the change of color and illumination, which causes a significant problem in face recognition using 2D intensity images. Also, 3D information from range images is much easier to utilize than from 3D meshes. Several previous approaches for face recognition using range images are focused on the data acquisition and preprocessing stage. On the other hand, this project will focus on the recognition stage itself. Previous approaches can be grouped into two types: geometrical and statistical. The geometrical approach uses curvature information of faces and the statistical approach uses subspace analysis, such as principal component analysis (PCA). A new algorithm based on the combination of two types of approaches will be presented in this project. This algorithm will extract the curvature information from range images first and apply PCA to reduce the dimension of feature space. Range images for experiments will be generated from a 3D mesh face database, *gavabDB*.

I. INTRODUCTION

Human face recognition has received a great deal of attention in recent times and emerged as an active research area in response to numerous law enforcement and commercial applications [1]. The objective of face recognition is to develop an automatic system that can recognize the human face as accurately as humans do. The two important terms in the previous statement are *automatic* and *as accurately as humans do* . It means that a good face recognition system should require as little manual intervention as possible but does not need to be able to distinguish faces which even people cannot distinguish.

With recent advances in image capture techniques and devices, various types of face-image data have been utilized and various algorithms have been developed for each type of image data [2]. Among various types of face images, a 2D intensity image has been the most popular and common image data used for face recognition because it is easy to acquire and utilize (Fig. 1). It, however, has the intrinsic problem that it is vulnerable to the change of illumination. Sometimes the change of illumination gives more difference than the change of people, which severely degrades the recognition performance. Therefore, illumination-controlled images are required to avoid such an undesirable situation when 2D intensity images are used. To overcome the limitation of 2D intensity images, 3D images are being used, such as 3D meshes and range images (Fig. 1). A 3D mesh image is the best 2D representation of 3D objects. It contains

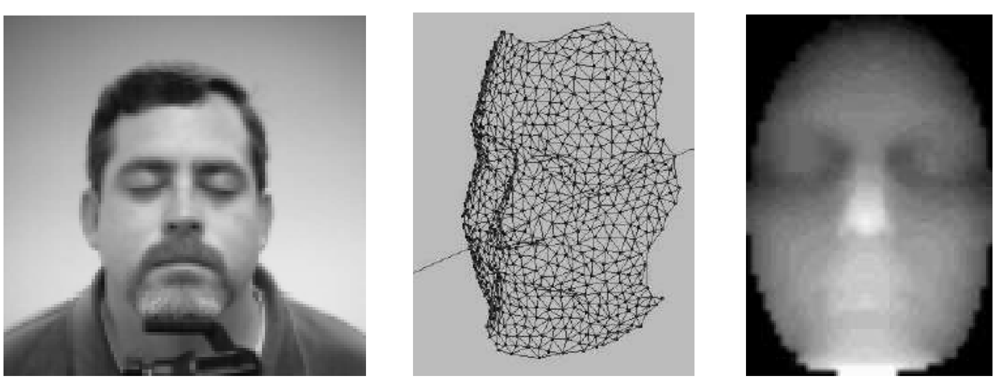

Fig. 1. Face images; 2D intensity image, 3D mesh image, and range image [3]

3D structural information of the surface as well as the intensity information of each point. By utilizing the 3D structural information, the problem of vulnerability to the change of illumination can be solved. A 3D mesh image is suitable image data for face recognition, but it is complex and difficult to handle.

A range image can be a good alternative to a 3D mesh image. A range image is simply an image with depth information as shown in Fig. 1. In other words, a range image is an array of numbers where the numbers quantify the distances from the focal plane of the sensor to the surfaces of objects within the field of view along rays emanating from a regularly spaced grid [4]. For example, a nose tip is the closest point to the camera on a face, so it has the highest numerical value. Range images have some advantages over 2D intensity images and 3D mesh images. First, range images are robust to the change of illumination and color because the value on each point represents the depth value which does not depend on illumination or color. Also, range images are simple representations of 3D information. The 3D information in 3D mesh images is useful in face recognition, but it is difficult to handle. Different from 3D mesh images, it is easy to utilize the 3D information of range images because the 3D information of each point is explicit on a regularly spaced grid. Due to these advantages, range images are very promising in face recognition.

Previous approaches based on range images can be divided into two categories: geometrical and statistical. The geometrical approach utilizes curvature information of faces, which was proposed by Besl and Jain [4] as a solution for a 3D object recognition problem. Gordon [5] used principal curvatures for a face recognition problem but did not explicitly show how to extract specific features. Tanaka and Ikeda [6] presented a better approach using curvature information. They construct extended Gaussian images (EGI) [7] of feature vector sets by mapping principal curvatures on unit spheres and use them as face representations. On the other hand, the statistical approach is based on subspace analysis. Achermann *et al.* [8] and Hesher *et al.* [3] applied the Eigenface method to a set of range images. The Eigenface method was originally proposed by

Turk and Pentland [9] for 2D face recognition, which is a method based on PCA. Liu *et al.* [10] presented a technique for finding linear representations of images that are optimal for specific tasks and specific data sets, instead of choosing a standard subspace analysis technique. They extended this work to range images [11]. The recognition rates of the statistical approaches are at the acceptable level, but the computational complexity is quite high.

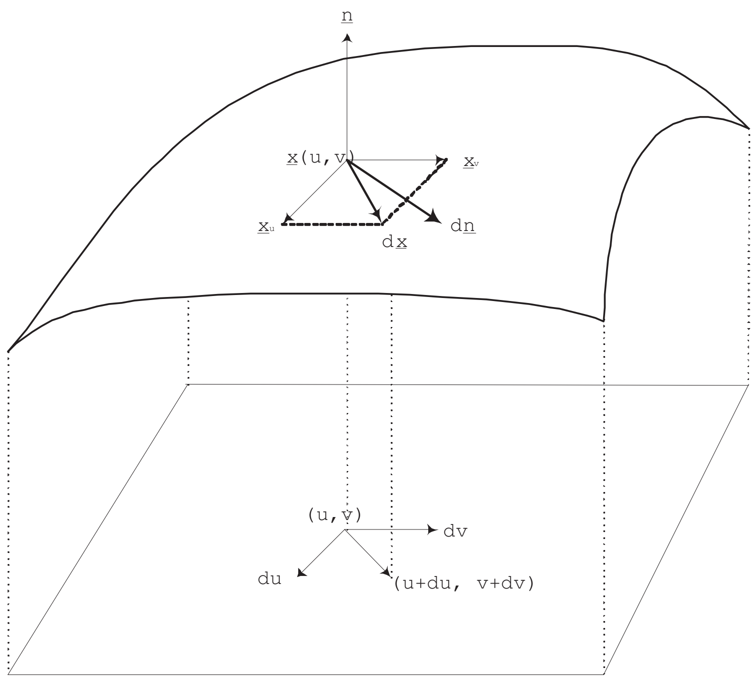

Fig. 2. Local coordinate frame at surface point [4]

II. Curvature Calculation

The best advantage of a range image is that the curvature information can be extracted and analyzed easily, which is invariant to illumination and viewpoint. There are several ways to represent the curvature information at a surface point. Among those, the *principal curvature* will be used as a representation in this project.

We define the *principal curvature* by introducing the fundamental forms of a surface in terms of the general explicit surface parameterization $\mathbf{x}(u, v)$ (Fig. 2). The first fundamental form I and the second fundamental form II of a surface defined by $\mathbf{x}(u, v)$ are given by the following forms:

$$I(u, v, du, dv) = d\mathbf{x} \cdot d\mathbf{x},$$

$$II(u, v, du, dv) = -d\mathbf{x} \cdot d\mathbf{n},$$

where $d\mathbf{x}$ is the change of the surface position and $d\mathbf{n}$ of the change in the normal vector. The ratio of $II(u, v, du, dv)/I(u, v, du, dv)$ is the normal curvature function κ_{normal} at a surface point, which is the function of the direction of the differential vector (du, dv). The maxima and minima of the normal curvature function are *principal curvatures*, which occur in the direction where $d\mathbf{x}$ and $d\mathbf{n}$ are aligned. The calculation of the principal curvatures, $\kappa_{1,2}$ are shown in Eq. 1 - Eq. 3;

$$K = \frac{f_{uu} f_{vv} - f_{uv}}{(1 + f_u^2 + f_v^2)^2} \tag{1}$$

$$H = \frac{1}{2} \cdot \frac{f_{uu} + f_{vv} + f_{uu} f_v^2 + f_{vv} f_u^2 - 2 f_u f_v f_{uv}}{(1 + f_u^2 + f_v^2)^{3/2}} \tag{2}$$

$$\kappa_{1,2} = H \pm \sqrt{H^2 - K}, \tag{3}$$

where

$$\mathbf{x} = (u, v, f(u, v)),$$

$$f_u = \frac{\partial f}{\partial u},\ f_v = \frac{\partial f}{\partial v},\ f_{uu} = \frac{\partial^2 f}{\partial u^2},\ f_{vv} = \frac{\partial^2 f}{\partial v^2},\ f_{uv} = \frac{\partial^2 f}{\partial u \partial v}.$$

Due to the first and second derivatives, the calculation of the principal curvatures is very sensitive to noise. Therefore, a smoothing filter should be applied to range images before the principal curvatures are calculated. Also, the derivatives should be estimated because range images have discrete values. Instead of direct numerical differentiation, we will determine a continuous differentiable function that best fits the surface within a small window of the range image, compute the derivatives of the continuous function, and evaluate them at the given discrete points. The reason why a small window is used instead of the whole image is to reduce the computational complexity. The detail of this estimation process is shown in [4].

III. Proposed Method

First, we will compute principal curvatures from range images and use the magnitude of principal curvatures. As a result, we will have a maximum curvature map and a minimum curvature map which are of the same size as the original range images. Since their size is still too large to be used for classification, we will apply the Eigenface method to these principal curvature maps. The Eigenface method is to apply PCA to a set of face images to reduce the dimension of feature space. Thanks to its computational efficiency, it is widely used for various types of face recognition problems. The detailed implementation of the Eigenface method is based on [9]. As a result of PCA, we will have two vectors of numerical values which will be the features of each image. As a last step, a simple nearest neighborhood (NN) classifier will be used for classification. The whole feature extraction process is summarized in Fig. 3.

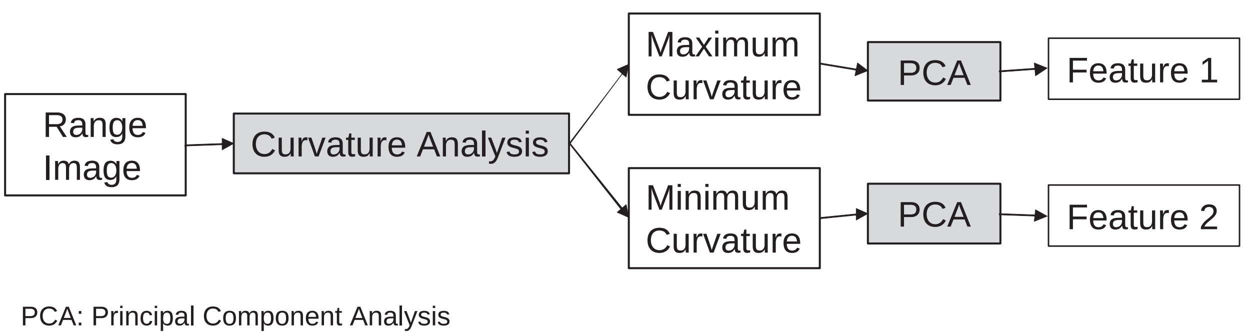

Fig. 3. Diagram of the feature extraction process

IV. Experimental Results

Range images are generated from a 3D face image database, *GavabDB*, which is built by Moreno *et al.* [12]. It contains 427 3D facial surface images corresponding to 61 individuals (45 male and 16 female) with 7 different images per a person. The images in this database were captured by Minolta VI-700 digitizer which generates a 3D surface mesh of the visible face surface. Nose tip positions and nose lines are used for normalization of range images. The nose tip position is extracted as the highest point in a range image. All images are translated so that the nose tip position matches the center of an image. Then, the nose tip values are adjusted for all images to have the same value; i.e., the nose tips of all faces get positioned at the same point in all three dimensions.

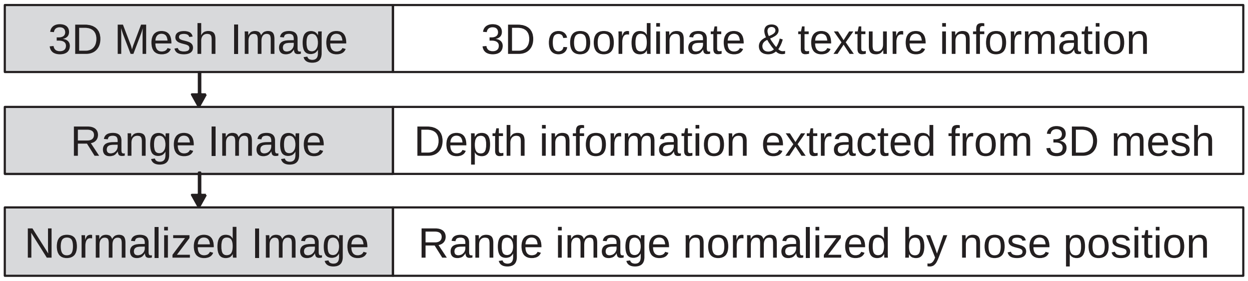

Fig. 4. Diagram of pre-processing process

The result of the experiment is shown in Table I. The recognition rate is generated by computing the ratio between the number of correct classifications and the total number of images and averaging it through several experiments. There is slight improvement of the recognition rate when the curvature maps are used.

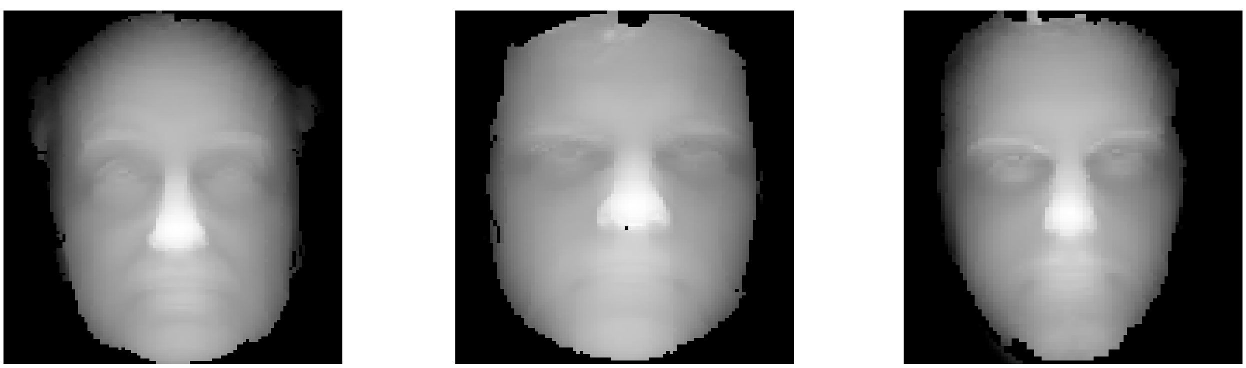

Fig. 5. Example of normalized range images

Data	Range Image	Curvature Map
Recognition Rate	73.77 %	78.69 %

TABLE I
COMPARISON OF RECOGNITION RATES

V. Discussion

From the result above, we can see that the method using curvature maps performs better than one with just range images in the recognition-rate sense, while the computational complexity is slightly increased. Even though the extraction of the curvature information requires a significant amount of computation, the computational complexity is not increased as much because the normalization step for this method is simpler. Since the performance of the Eigenface method is fairly dependent on how well images are normalized, the normalization step should be enough delicate to handle such details as the slight change of face upward/downward or left/right, which requires a large amount of computation. The normalization step for this method does not need to be as complex as that for the Eigenface method, so the overall computational complexity is not severely changed. Therefore, we conclude that the curvature information of range images is able to play an important role in the face recognition problem.

There are, however, a couple of things that should be done to improve this project. First, due to the poor normalization process done for this experiment, we could not perform various types of experiments, such as experiments with different facial expressions and rotations, and only the experiment for frontal images with neutral expressions was done. More complete normalization process will enable us to perform more types of comparison and analysis. Also, the quantitative method to compare the computational complexity should be devised. Since we did not have any quantitative method, we could compare the complexity only qualitatively. Among various kinds of curvature information, only the magnitude of principal curvatures is used as a feature in this project. Other curvature information, such as the *Gaussian curvature* and *mean curvature*, is generated at the same time when the principal curvatures are computed. So, using those curvatures does not increase the computational complexity. We will investigate the recognition performance when other curvatures are used with principal curvatures.

REFERENCES

[1] R. Chellapa, C. Wilson, and S. Sirohey, “Human and machine recognition of faces: A survey,” *Proc. of the IEEE*, vol. 83, no. 5, pp. 704–740, May 1995.

[2] K. Chang, P. Flynn, and K. Bower, “Multi-modal 2D and 3D biometrics for face recognition,” in *Proc. IEEE Int. Workshop on Analysis and Modeling of Faces and Gestures*, Oct. 2003, pp. 187–194.

[3] C. Hesher, A. Srivastava, and G. Erlebacher, “A novel technique for face recognition using range imaging,” in *Proc. IEEE Int. Symposium on Signal Processing and Its Applications*, July 2003, pp. 201–204.

[4] P. Besl and R. Jain, “Invariant surface characteristics for 3D object recognition in range images,” *Computer Vision, Graphics, and Image Processing*, vol. 33, pp. 33–80, 1986.

[5] G. Gordon, “Face recognition based on depth maps and surface curvature,” *Geometric Methods in Computer Vision*, vol. SPIE 1570, pp. 1–12, July 1991.

[6] H. Tanaka and M. Ikeda, “Curvature-based face surface recognition using spherical correlation - principal directions for curved object recognition,” in *Proc. IEEE Int. Conf. on Automated Face and Gesture Recognition*, Apr. 1998, pp. 372–377.

[7] B. Horn, *Robot Vision*. The MIT Press, 1986.

[8] B. Achermann, X. Jiang, and H. Bunke, “Face recognition using range images,” in *Proc. IEEE Int. Conf. on Virtual Systems and Multimedia*, Sept. 1997, pp. 129–136.

[9] M. Turk and A. Pentland, “Eigenfaces for recognition,” *Journal of Cognitive Neuroscience*, vol. 3, no. 1, pp. 71–86, 1991.

[10] X. Liu, A. Srivastava, and K. Gallivan, “Optimal linear representations of images for object recognition,” *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 26, no. 5, pp. 662–666, 2004.

[11] A. Srivastava, X. Liu, and C. Hesher, “Face recognition using opimal linear components of range images,” *Journal of Image and Vision Computing*, accepted in 2003, http://www.cavis.fsu.edu/.

[12] A. Moreno and A. Sanchez, “GavabDB: a 3D face database,” in *Proc. COST275 Workshop on Biometrics on the Internet*, Mar. 2004, pp. 75–80.