A Novel Technique of Feature Extraction for 3-D Face Recognition

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ABSTRACT

Various techniques are available for extracting curves form 3D meshes. Instead of extracting curves form 3D meshes directly, in this paper we apply principal mean curvature approach and then compute Discrete Wavelet Transform (DWT) to extract facial profile. This approach is much more efficient and robust compared to extracting curves form the mesh data. Once the Extraction of geometric Curvature information from 3D facial surface is done, then next step is to perform 3D face recognition using LDA, a non-fiducial method as these are often unreliable. The feature level fusion prior to LDA improves the recognition rate considerably. Basel 3-D face scans database is used for demonstrating this approach.

Keywords— *3D face recognition, DWT, principal mean curvature, feature extraction, matching.*

INTRODUCTION

Face recognition techniques mainly come from computer vision, pattern recognition and artificial intelligence and employing the face as a biometric feature has been used in many application scenarios. In its early days, most face recognition algorithms used 2D intensity or colour images. As the accuracy of 2D face recognition is adversely affected by variations in pose, expression, illumination, and occlusions, the development of robust, fully-automatic 2D face recognition system remains a challenging problem. Alternatively, using 3D facial data to understand the characteristics of the human face in the 3D domain has been shown to have much promise for improving the overall recognition performance.

Using 3D face as a biometric has many advantages in comparison with 2D imaging:

(1) 3D face shape possesses high distinctiveness among different identities, which can be extracted from various types of 3D shape representations in terms of depth, surface normal, curvatures and so forth. Some specific regions, for example the nose, have been shown to contain lots of discriminative features [3-5].

(2) 3D acquisition systems have the potential to solve the illumination problem of 2D imaging as feature detection and the consistency of feature extraction by 2D captures fail in different illumination conditions.

(3) Compared to 2D methods, 3D facial shape provides more possibilities to address the problems caused by expression, pose and occlusion variations. Feature extraction on some relatively rigid regions, for example of 3D nose or certain small facial patches, is one of the most popular approaches to address expression variations. Also, it is easy to calibrate pose variations on the 3D shape and the missing areas caused by occlusions can be estimated from the known areas.

Although 3D strategies have the potential to address many drawbacks of 2D imaging and improve the recognition performance of biometric systems, there are still many challenging and unsolved issues in 3D face recognition, including the expression robust feature extraction, low complexity and accurate pose calibration, and real world applications. Expression invariant 3D face recognition requires developing more effective and efficient descriptors for feature extraction on the 3D shape or evaluating some rigid patches on the face, which suffer less facial surface changes or movements under expressions. For the pose calibration, extracting pose invariant features and making a compromise between the efficiency and accuracy are two hot topics in 3D face recognition.

In this paper we focus on performing human recognition from 3-D face images. We calculate the mean curvature of the 3-D face. Subsequently, the Discrete Wavelet Transform has been computed for directional feature extraction. The mean and standard deviation features are fused to obtain state of the art classification performance. The paper is organized as follows:

LITERATURE SURVEY

The activity to exploit 3D data to improve the accuracy and robustness of face recognition system is still weakly addressed. Only a few works on the use of 3D data have been reported. These methods can be categorized into four groups: Methods based on curvature analysis, methods by shape representation, methods by model fitting and image synthesis, and other methods.

Many of the early studies concentrate on curvature analysis. Lee et al.[2] propose a method to detect corresponding regions in two range images by graph matching based on Extended Gaussian Image (EGI). A match between a region in a probe image and in a gallery image is done by correlating EGIs. Tanaka et al.[2] perform curvature-based segmentation and represent the face using an Extended Gaussian image (EGI). For each face, two EGIs are constructed from maximum principal curvature and minimum principal curvature.

A few researchers attempt to use a shape representation to analyze the 3D facial data. Chua et al. describes a technique for 3D face recognition based on Point Signature — a representation for free-form surfaces, which is also highly dependent on the quality of facial range data [3]. Chua et. al. in their work[4] combines Point Signature on 3D range data and Gabor filter response on 2D grayscale image for facial feature detection and recognition. The 2D and 3D features together form a feature vector. Pan et al. [5] experiment with 3D face recognition using both a Hausdorff distance approach and a PCA-based approach. They present a novel signature for pose-invariant detection of facial feature from range data. The third kind of approach is to use model fitting or image synthesis to cope with the influence of illumination and pose. Lee et al. [6], employ an edge model and a color region model to analyze face image, and a wireframe model to synthesize the face image in virtual view for recognition. Also, this type of approach does not involve the sensing or matching of 3D shape descriptions. And Zhao et al. present a method to synthesize the virtual image with SFS-based 3D shape recovery [7]. For this kind of approach, the input is a 2D face image but not 3D data.

For recognition using facial profile, many methods have been performed. Many of the previous work carried out depends on fiducial points extracted by heuristic rules. The work presented by Ansari and Abdel-Mottaleb [8] could be considered as an example of this kind of methods. Starting from one frontal and one profile view image, they use 3D coordinates of a set of facial feature points to deform a morphable model fitting the real facial surface. The Iterative Closest Point (ICP) algorithm by Besl and McKay [9] is often used as an alternative approach aligning models. Medioni and Waupotitsch [10] proposed an ICP-based approach, which aligns two face surfaces to calculate a map of differences between the facial surfaces. Then statistic measures are applied in order to obtain a compact description of this map. Indeed, the work of Lu et al. [11] is headed in this direction. They describe both a procedure for constructing a database of 3D mesh models from several 2.5D images and a recognition method based on ICP algorithm. Hesher et al. [12] use a fast and simple algorithm for approximately calculating the principal components of a dataset and so reducing the dimensionality. They explore principal component analysis (PCA) style approaches using different numbers of eigenvectors and image sizes

PROPOSED SYSTEM

The proposed classification of 3-D face recognition system is carried out using Basel 3-D face scans database. We referred "A 3D Face Model for Pose and Illumination Invariant Face Recognition"[49] and acknowledge Prof. Dr. T. Vetter, Department of Computer Science, and the University of Basel. It consists of 10 face scans with full 3-D view.

With data augmentation, two more view in addition to the 00, which are $+10^0$ and -10^0 are generated. The database is of 3D images of 30 persons. These 3D face images are used as training dataset for the classifier.

The proposed system also deals with the issues of existing system such as distortion and noise. In addition, it also reduces the computational complexity of the system. Fig. 1 shows the block diagram of our proposed system

Preprocessing involves the image enhancement and image resizing. These are required to make system robust and ensure faster response in real time.

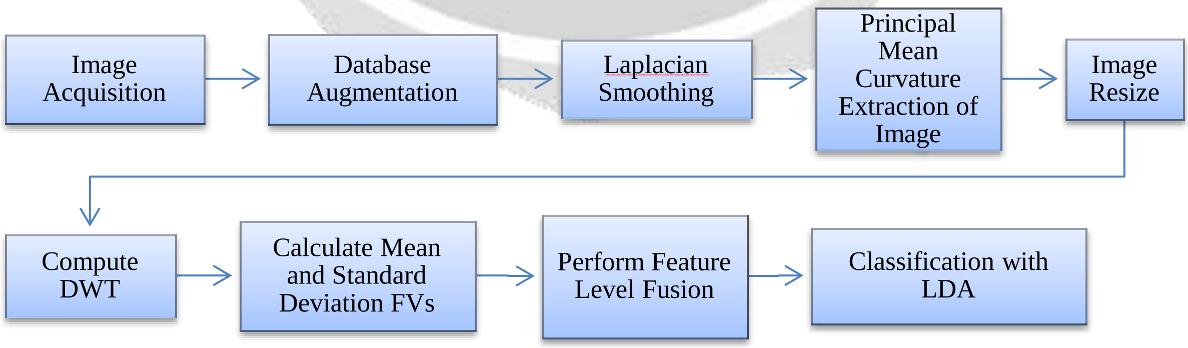


Fig.1: Proposed system

The Laplacian smoothing removes the high frequency noise components and thus enhances the image. Fig. 2 is the original image and Fig.3 is the output after Laplacian smoothing operation

Fig.2: Sample Face from Basel 3-D Face Scans Database

Fig.3: Laplacian Smoothing Operation

Principal Mean Curvature Extraction Image of the Laplacian smothered image is the created by using Open source Meshlab tool.This memo records the formulas for calculating the principal curvatures of a surface parameterized in the form z = f (x, y).

First compute the Gaussian curvature

$$K = \frac{f_{xx}f_{yy} - f_{xy}^2}{(1 + f_x^2 + f_y^2)^2} \ldots\ldots\ldots\ldots\ldots\ldots.\ldots(1)$$

Then Mean curvature is computed using the below equation

$$H = \frac{(1+f_x^2)f_{yy} + (1+f_y^2)\, f_{xx} - 2 f_x f_y f_{xy}}{2(1+f_x^2+f_y^2)^{3/2}} \ldots\ldots(2)$$

The principal curvatures k1 and k2 are then found using

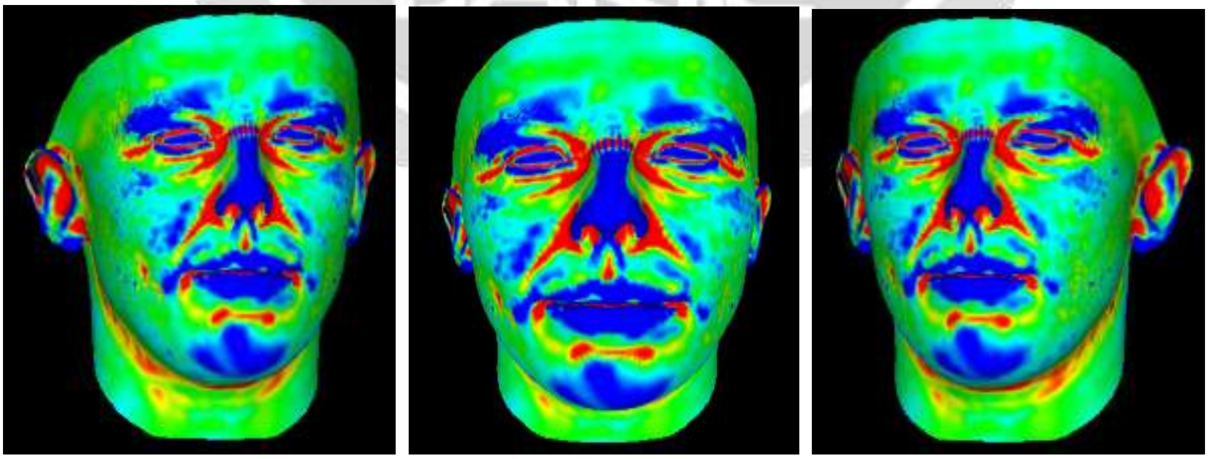
$$k_1 = H + \sqrt{H^2 - K} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

$$k_2 = H - \sqrt{H^2 - K} \ldots\ldots\ldots\ldots\ldots..\ldots(4)$$

and the principal radii of curvature are calculated as

$$r_i = \left| {}^{1}/_{k_i} \right|, \quad i = 1,2 \ldots\ldots\ldots\ldots\ldots\ldots(5)$$

The minimum of the two principal radii of curvature is the minimum radius of curvature of the surface at the given point. Each individual image resized 128x128 is applied with principal mean curvature extraction is produced with pose variation at +10 degrees and –10 degree angle as shown in Fig.5 and Fig.6 respectively.



(a) (b) (c)

Fig.4: Principal Mean Curvature Operation at (a)+10 degree (b) 0 degrees (c) -10 degrees

6. RESULT AND DISCUSSION

The proposed classification of 3-D face recognition system is carried out using Basel 3-D face scans database.

It consists of 10 face scans with full 3-D view. With data augmentation, two more view in addition to the 0^0, which are $+10^0$ and -10^0 are generated. All these images are subjected to feature extraction using Discrete Wavelet Transform with Haar basis function to produce low frequency abstract component (fig.7 cA) and high frequency horizontal, vertical and diagonal components (fig.8 cH, fig.9 cV, fig.10 cD). We have used 5 fold cross validation.

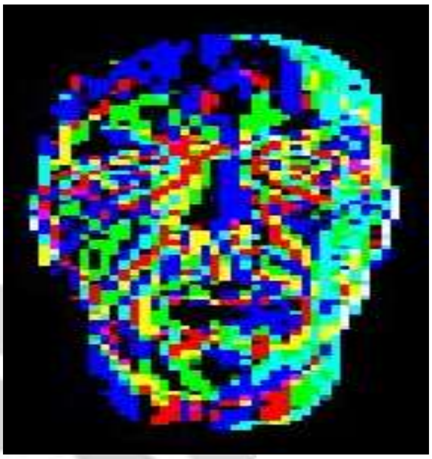
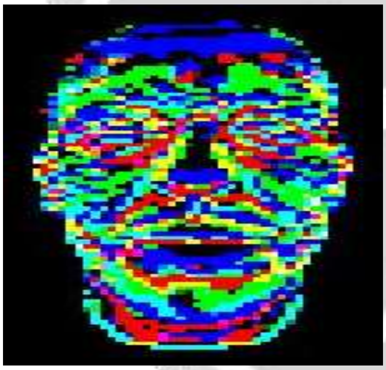


Fig.5: Haar output Image for Abstract component cA **Fig.6**: Haar output Image for Horizontal component cH

A feature level fusion performed to compute the final feature vector from mean and standard deviation feature vectors. The final feature vector composed of the mean and standard deviation feature vectors used for classification using Linear Discriminant Analysis (LDA). As discussed in previous section LDA used to transform the features into a lower dimensional space, which maximizes the ratio of the between-class variance to the within-class variance, thereby guaranteeing maximum class separability.



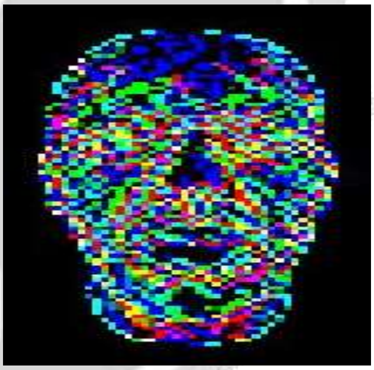


Fig.7: Haar output Image for Vertical component cV Fig.8: Haar output Image for Diagonal component Cd

The confusion matrix in Image 5.5 verifies the excellent performance of the classifier. All the three images for 10 persons of from the database are accurately and convincingly predicted by the proposed classifier.

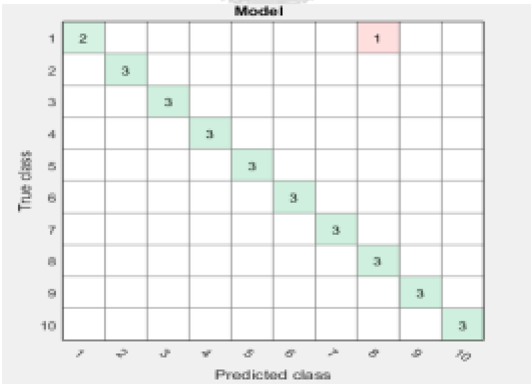


Fig.9: Confusion Matrix

The ROC (Receiver Operating Characteristics) curve for the dataset images ROC curve is closer to the left-hand border and then the top border of the ROC space. This confirms the accuracy of the tests in Image 5.6. Image 5.7 is ROC curve for class 2-10 where the AUC (Area under the curve) shows 100% accuracy

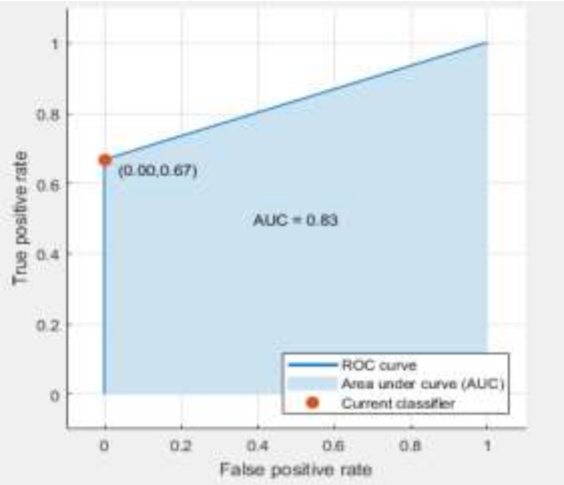


Fig.10: ROC curve for Class 1

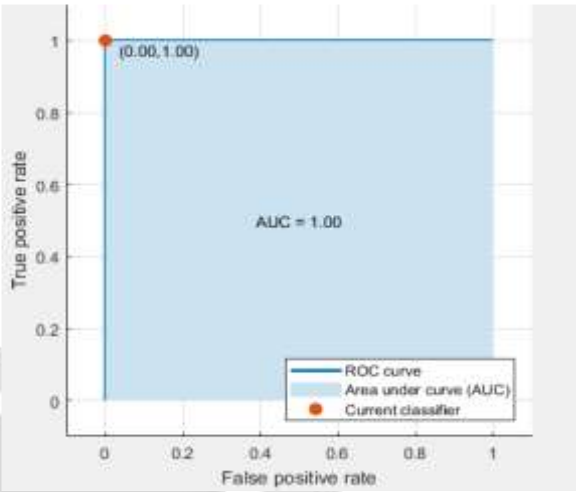


Fig.11: ROC curve for remaining classes (2-10)

Table 5.1 compare the performance of the fusion of the features extracted using mean and standard deviation with the performance of the individual methods. The improvement in rate of recognition is high and affirms the effectiveness of the proposed methodology.

Table 1: Recognition Performance

Feature extraction Method	LDA NN
Mean	70.0%
Standard Deviation	86.7%
Fusion	96.7%

5. CONCLUSION

This paper has investigated face recognition from range data by feature extraction using Discrete Wavelet Transform with Haar basis function. Linear Discriminant Analysis used post the feature level fusion results in excellent accuracy of 96.7% for face recognition. The approach works similar accuracy even in case of non-frontal orientation of image acquisition.

The proposed methods are carried out on the Basel 3-D face scans database, a facial range data database with limited quality. The experimental results show that the proposed surface matching and profile matching are competitive, and outperform several excellent appearance-based face recognition methods.

Recognizing faces across pose and illumination still a hard problem. The pose and illumination variation are two challenges in 2D image-based face recognition. Recognizing from 3D data is likely to solve the two problems. Despite variant of head pose, the viewpoint is more easily recovered from range data rather than from 2D images.

Moreover, if acquisition of range data is not considered, lighting condition has no effect on our approach. 3D Face recognition from range data is promising. In the future, experiments on a more accurate database are expected. Tackling facial expression problem is also another work in the future.

6. REFERENCES

[1] J. C. Lee and E. Milios, “Matching range images of human faces,” in Proc. IEEE International Conference on Computer Vision, pp. 722–726 (1990).

[2] H. T. Tanaka, M. Ikeda and H. Chiaki, “Curvature-based face surface recognition using spherical correlation — principal direcions for curved object recognition,” in Proceedings of IEEE International Conference on Automatic Face and Gesture Recognition, pp. 372–377 (1998).

[3] M.-H. Yang, “Kernel eigenfaces vs. kernel fisherfaces: Face recognition using kernel methods,” in Proc. IEEE International Conference on Automatic Face and Gesture Recognition, pp. 215–220 (2002).

[4] Y. Wang, C.-S. Chua and Y.-K. Ho, "Facial feature detection and face recognition from 2D and 3D images," Pattern Recognition Letters 23, 1191–1202 (2002).
[5] G. Pan, Y. Wang and Z. Wu, "Pose-invariant detection of facial features from range data," in Proceedings of IEEE International Conference on Systems, Man, and Cybernetics, Hyatt Regency, Washington D.C., pp. 4171–4175 (2003).
[6] M. W. Lee and S. Ranganath, "Pose-invariant face recognition using a 3D deformable model," Pattern Recognition 36(8), 1835–1846 (2003).
[7] W. Zhao and R. Chellappa, "Illumination-insensitive face recognition using symmetric shape-from-shading," in Proc. IEEE International Conference on Computer Vision, pp. 1286–1293 (2000).
[8] Ansari, A., Abdel-Mottaleb, M., 2003. 3-D face modeling using two views and a generic face model with application to 3-D face recognition. In: Proc. IEEE Conf. on Advanced Video and Signal Based Surveillance (AVSS 2003) Miami, FL, USA, July, pp. 37–44.
[9] Besl, P.J., McKay, N.D., 1992. A method for registration of 3-d shapes. IEEE Trans. Pattern Anal. Machine Intell. 14 (2), 239–256
[10] Medioni, G., Waupotitsch, R., 2003. Face recognition and modeling in 3D. In: Proc. IEEE Internat. Workshop on Analysis and Modeling of Faces and Gesture Recognition (AMFG'03). Nice, France, October, pp. 232–233.
[11] Lu, X., Colbry, D., Jain, A.K., 2004. Three-dimensional model based face recognition. In: Proc. 17th Internat. Conf. on Pattern Recognition (ICPR2004), Cambridge, pp. 362–366.
[12] Hesher, C., Srivastava, A., Erlebacher, G., 2002. Principal component analysis of range images for facial recognition. In: Proc. Internat.Conf. on Imaging Science, Systems and Technology (CISST 2002).