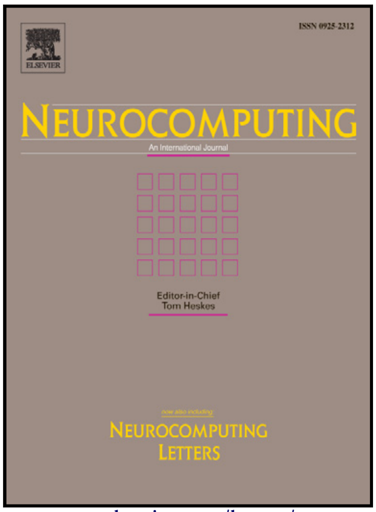

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Study on Novel Curvature Features for 3D Fingerprint Recognition

Feng Liu[1], and David Zhang[2], *Fellow, IEEE*

Abstract – The human finger is a three-dimensional object. More information will be provided if 3D fingerprint images are available compared with 2D fingerprints. This paper explores 3D fingerprint features, as well as their possible applications. Novel fingerprint features, which are defined as Curvature Features (e.g. curve-skeleton, overall maximum curvatures), are for the first time proposed and investigated in this paper. Those features are then employed to assist more accurate fingerprint matching or classify human gender after analyzing their characteristics. A series of experiments are conducted to evaluate the effectiveness of employing these novel fingerprint features to fingerprint recognition based on the established database with 541 fingers. Results show that an Equal error Rate (EER) of ~15% can be achieved when only curve-skeleton is used for recognition. But, promising EER of ~3.4% is realized by combining curve-skeleton with classical 2D fingerprint features for recognition that indicates the prospect of 3D fingerprint recognition. The proposed overall maximum curvatures are found to be helpful for human gender classification.

***Index Terms* —** Touchless fingerprint recognition, curvature fingerprint features, curve-skeleton, gender classification, overall maximum curvatures

I. INTRODUCTION

As one of the most widely used biometrics, fingerprint has been investigated for more than a century [1]. Effective Automated Fingerprint Recognition Systems (AFRSs) are available with the rapid development of fingerprint acquisition devices and the advent of many advanced fingerprint recognition algorithms. However, they are almost based on 2D fingerprint features, even though the fact is that the human finger is a 3D object. There are

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distortions and deformations introduced and 3D information lost when 2D fingerprint images are used, which cannot perfectly meet people's demands in accuracy and computational complexity. Developing user-friendly AFRSs with high precision and high efficiency is still an open issue in fingerprint recognition domain.

With the expansion of acquisition technology, 3D biometric authentication techniques come into researchers' view in recent years, such as 3D face [2-3], 3D ear [4-6] and 3D palmprint recognition [7-10]. For 3D fingerprints, even though there are some works about 3D fingerprint image acquisition and processing [11-12], they did not investigate the utility of 3D fingerprint features and did not report any experimental results of user authentication using the acquired biometric information. This has motivated us to explore the utility of 3D fingerprint features and the possibility of combining them with 2D features for fingerprint recognition. The contributions of this paper include: i) This paper, for the first time, investigates features on 3D fingerprint images, as well as the corresponding feature extraction and matching methods. More specifically, Curvature Features, such as curve-skeleton, overall maximum curvatures are firstly proposed and defined. Such features are then extracted by model fitting method. Finally, Iterative Closest Point (ICP) in 3D space is adopted for matching; ii) By analyzing their distinctiveness, 3D fingerprint curvature features are used for different applications. We found curve-skeleton are suitable for assisting fingerprint recognition while overall surface can be used for gender classification. Fusion strategy is employed to combine 2D and 3D fingerprint matching results to figure out the effectiveness of improving recognition accuracy by including 3D fingerprint features.

The organization of this paper is as follows. In Section II, Curvature features in 3D fingerprint images are defined. Section III firstly introduces the 3D fingerprint images we obtained and then describes the curvature features extraction and matching algorithms we used in detail. Case studies of such 3D fingerprint curvature features are introduced in

Section IV. Section V finally concludes this work and suggests future researches.

II. DEFINITION OF CURVATURE FEATURES IN 3D FINGERPRINT IMAGES

Fingerprints are distinguished by their features. In general, fingerprint features in 2D images are classified into three levels [13]. Level 1 features are defined as the macro details of fingerprints such as singular points and global ridge patterns, e.g. deltas and cores. They are mainly used for fingerprint classification or indexing rather than recognition since they are not very distinctive. Level 2 features are minutiae (ridge endings and bifurcations). Such features are the most distinctive and stable ones, which are used in almost all AFRSs [1, 13-14]. Level 3 features often refer to the dimensional attributes of the ridges including sweat pores and ridge edge features, which are used to assist more robust fingerprint recognition.

Fig. 1 shows a fingerprint image in 3D space, we can see that the above defined fingerprint features spread over different scales of depth. For example, core points are located in the center part of the finger with almost the highest depth value. Level 2 and Level 3 features which are closely related with the distribution of ridges actually possess more attributes in 3D space (e.g. depth value, ridge orientation along the depth direction). Thus, in 3D fingerprint image, features which are coarse than Level 1 features can be obtained (e.g. the contour of the finger). We defined such structural information in 3D fingerprint images as Curvature Fingerprint Features in this paper. They provide information of overall structure of humans' fingers and indicate the distribution of other features, such as the curve-skeleton [15] and overall maximum curvatures. The curve-skeleton feature depicts the thinned contour of finger shape, as shown in Fig. 1 (green and red lines). The overall maximum curvatures describe the maximal horizontal curvature and the maximal vertical curvature of the finger.

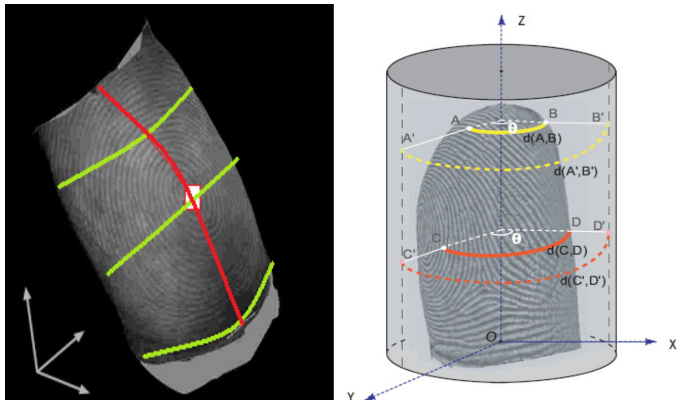


Fig. 1. Fingerprint image in 3D space.

III. CURVATURE FEATURES EXTRACTION AND MATCHING

A. Source of Our 3D Fingerprint Image

Currently, there are three frequently-used 3D imaging techniques, namely multi-view reconstruction [11, 16-17], laser scanning [18], and structured light scanning [12, 19-20]. Among them, the multi-view reconstruction technique has the advantage of low-cost but disadvantage of low accuracy. Laser scanning normally achieves high resolution 3D images but the cost is expensive and the collecting time is long. It is also very sensitive to the status (wet or dry) of the object. Structured light imaging is a 3D scanning technique which has moderate accuracy and cost, but it also takes long time to collect 3D data. It has the drawback of instability to move which means one should keep still when projecting some structured light patterns to the human finger. Considering the cost, friendliness, as well as just structural information needed, we choose to use multi-view reconstruction technique to acquire the 3D fingerprint image. The reconstruction results from a touchless multi-view fingerprint imaging device in our own designing and the 3D reconstruction techniques we proposed are introduced in our previous work [21, 22]. Fig. 2 shows the schematic diagram of our device, the captured images and the reconstructed 3D fingerprint image.

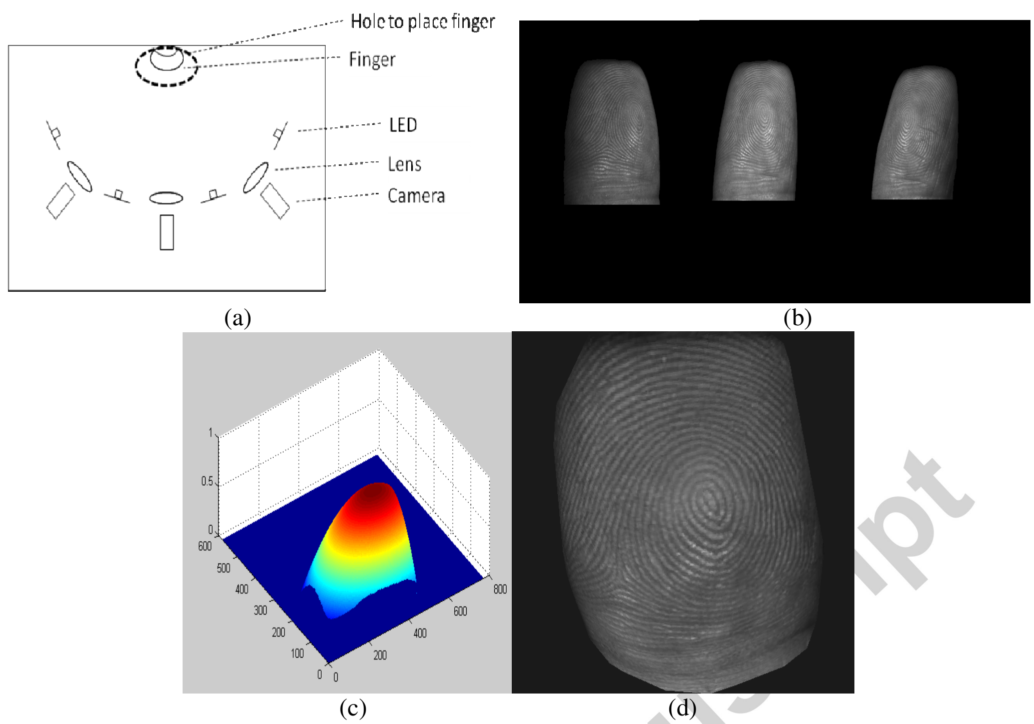


Fig. 2. Touchless multi-view fingerprint imaging device and the captured and reconstructed fingerprint images. (a) Schematic diagram of our touchless multi-view fingerprint capture device, (b) Preprocessed images of a finger captured by our device used to reconstruction (left, frontal, right), (c). Reconstructed 3D finger shape, (d) 3D fingerprint image.

B. Curvature Features Extraction

Since our 3D fingerprint image is reconstructed from multi-view fingerprint images, there is a one-to-one correspondence between the 3D points and the 2D fingerprint image pixels. Preprocessing such as Region of Interest (ROI) extraction and pose correction can be done in 2D fingerprint images, and implemented in 3D situation. The iterative thresholding segmentation method is used in this paper to extract ROI [23] (see Fig. 3(b)). Since it is difficult to control the way users putting their fingers when collecting fingerprint images (tilted fingerprint images, see Fig. 3(a)), pose correction is necessary. We accomplished it by simply rotating the original image as follows: i) Scan ROI horizontally and find the center point of each row (green dash line in Fig. 3(b)); ii) Fit such center points by a line (red solid line in Fig. 3(b)); iii) Calculate the angle between the fitted line and vertical axis (θ shown in Fig. 3(b)); iv) Rotate the image by θ anti-clockwise. Fig. 3(c) shows the final correct 2D fingerprint image and Fig. 3(e) shows the correct 3D finger shape of original 3D shape of Fig. 3(d).

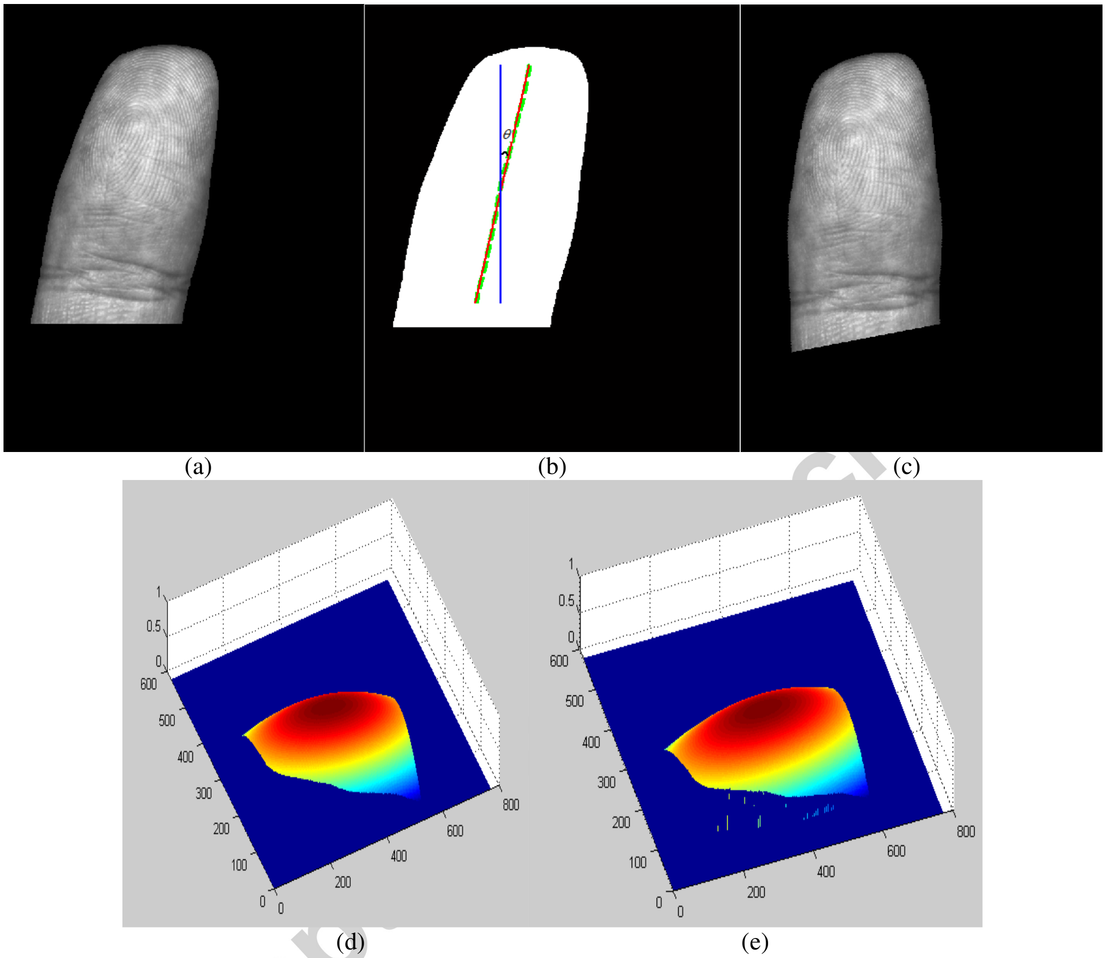


Fig. 3. Position Correction. (a) Original tilted fingerprint image, (b) ROI extraction of (a), (c) Fingerprint image after pose correction, (d) Original 3D finger shape, (e) Corrected 3D finger shape.

Given a corrected 3D fingerprint image, stable and unique features are expected to be extracted for the following pattern matching and recognition. 3D depth information reflects the overall structure of the human finger. However, there are many invalid points in the whole 3D finger shape due to the structure of the human finger. Wrinkles and scars in finger also affect the local structure of finger shape. Thus, we proposed to extract curve-skeleton of finger shape. As shown in Fig. 4, different 3D objects are almost fully represented by their curve-skeletons.

Since 3D finger shape model is close to binary quadratic function [22], profile of horizontal section can be fitted by parabola and reflects the changes of finger width, while vertical profile depicts variation tendency of depth from finger tip to distal interphalangeal crease. The curve-skeleton of 3D fingerprint image we used here is a medial axis/surface approach. It consists of representative vertical and horizontal lines. Since each horizontal profile is parabola-like shape, we extracted the extreme value of each fitted parabola line to form the representative vertical line (blue line in Fig. 5(a)). Three representative horizontal lines are selected at a certain step length (100). The distal interphalangeal crease is chosen as the baseline (see the green line in Fig. 5(a)). Fig. 5(b) shows the curve-skeleton we extracted from 3D finger depth map. For overall maximum curvatures, they can be easily calculated since our 3D finger shape is reconstructed by model fitting. The coefficients of the binary quadratic function control the maximal horizontal and vertical curvatures of 3D finger, namely the parameters of A and B in Eq. (1). Thus, these two coefficients of the binary quadratic function are maintained to represent the maximal horizontal and vertical curvatures, namely the defined overall maximum curvatures.

$$f(x, y) = Ax^2 + By^2 + Cxy + Dx + Ey + F \tag{1}$$

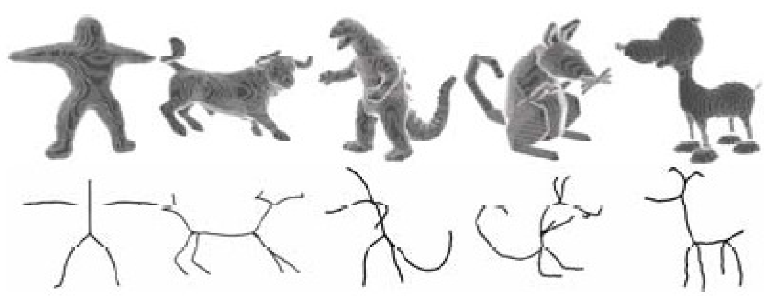
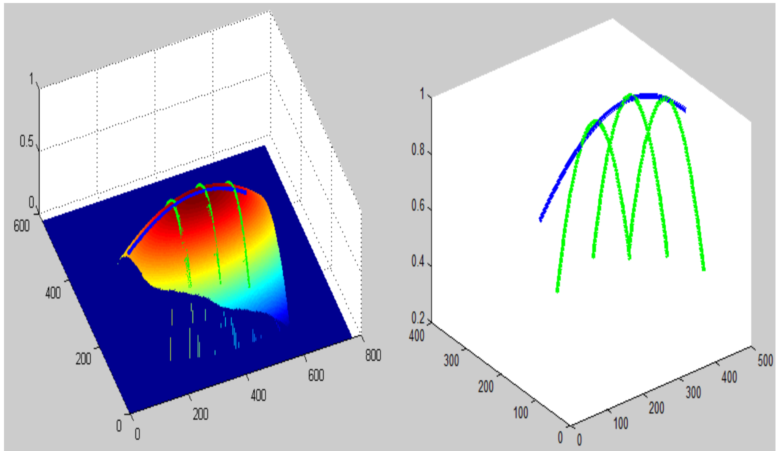


Fig. 4. Examples of curve-skeletons of different 3D objects.



(a) (b)

Fig. 5. Examples of curve-skeleton for 3D finger. (a) 3D finger shape, (b) Extracted curve-skeleton.

C. Curvature Features Matching

From Fig. 5(b), we can see that curve-skeleton consists of several 3D lines. Intuitively, the iterative closest point (ICP) algorithm is suitable for solving such matching problem. ICP method [24, 26-30] is widely used in many 3D object recognition systems for matching. In this paper, we slightly modified the ICP method to measure the distances between two sets of points. The algorithm is given in the box below and Fig. 6 shows an example of matching two curve-skeletons by our modified ICP method.

1. Input: Model point set: D_1; Test point set D_2;
2. Parameters initialization: stop criterion for distance T*d*=0.1; intial rotation matrix R_0=I; initaltranslation vector $T_0=[0\ 0\ 0]^T$;
3. While (new correspondences set found between D_1 and D_2))

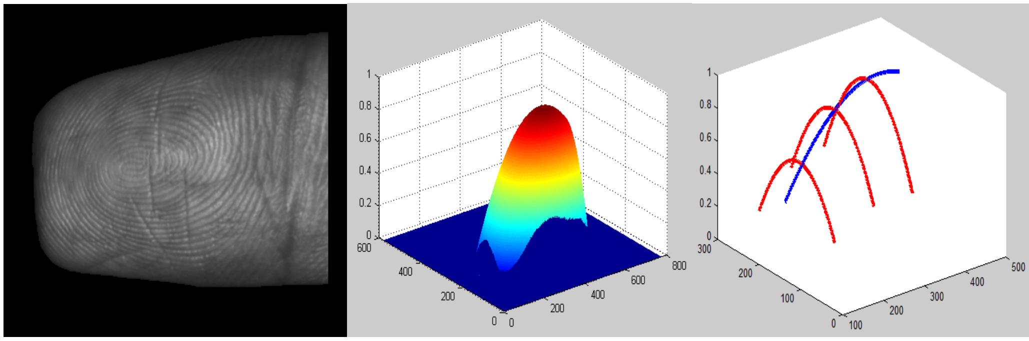
   { [corr, D_i]=dsearchn(D_1 , D_2);

   $K_i=D_i>Td$;

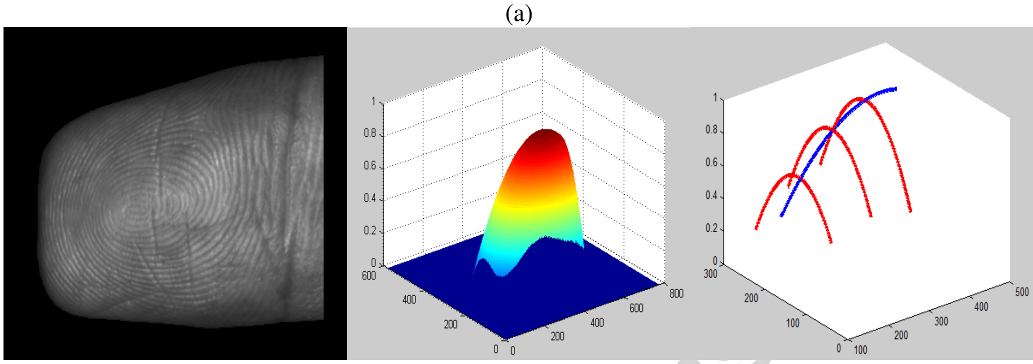
   Discard corr(K_i);

   Update R_i, T_i;

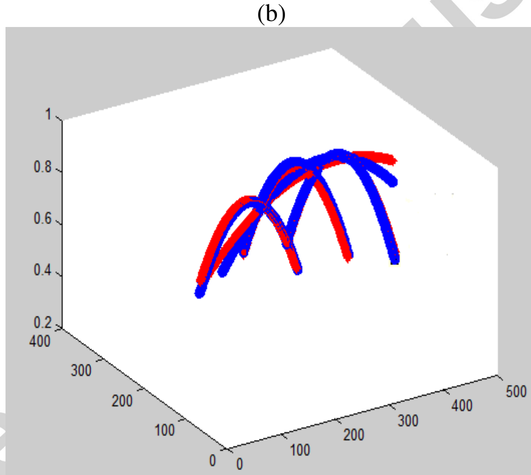
   $D_2=R_i* D_2+T_i$;}
4. Output: distance vector D, registered D_2, rigid transform paramters: R and T.



(a)



(b)



(c)

Fig. 6. Example of curve-skeleton matching by icp method. (a) The model 2D fingerprint image, 3D finger shape, and extracted curve-skeleton feature, (b) The test 2D fingerprint image, 3D finger shape, and extracted curve-skeleton feature, (c) Matching result by ICP method.

Overall maximum curvatures are represented by single values, which can be taken as match scores directly. Thus, they can be compared directly after they are extracted.

IV. CASE STUDIES

A. Database

It is notable that our 3D fingerprint images consist of the reconstruction results from a touchless multi-view fingerprint imaging device designed by ourselves. The 3D reconstruction techniques we proposed is introduced in our previous work [22]. Our experiments are then implemented on our reconstructed 3D fingerprint Database with 541 fingers. Since the public touchless multiview fingerprint databases, which are used to reconstruct 3D fingerprints, are unavailable, the database is established by us. The fingerprint images are collected from ordinary people in our college, aged 22-45. The volunteers include 223 female fingers and 318 male. All five human fingers are included. For each finger, there are 2 pictures which captured at separate sessions from one week to several months.

B. Case 1: Curve-skeleton based Recognition

To study the distinctiveness of curve-skeleton features of human fingers, we show examples of matching results of different genders and different fingers. As shown in Table I, examples of curve-skeletons from a female and a male with thumb, index finger and little finger captured at different sessions are given.

We then matched them by ICP method. The percentage of matched points (Pm) and the mean distance between matched pairs (Mdist) are taken as the match score. We firstly matched the curve-skeletons from the same finger but captured at different time, as listed in Table II. Results show that the mean distance between matched pairs are smaller than 1 and the percentage of matched points are larger than 70%. Fig. 7 also shows the matching results of different genders and finger types, the match scores are listed in Table III. The results show that big difference existed between different fingers and different genders in curve-skeleton, since such feature reflects the finger width feature and curvatures of fingers.

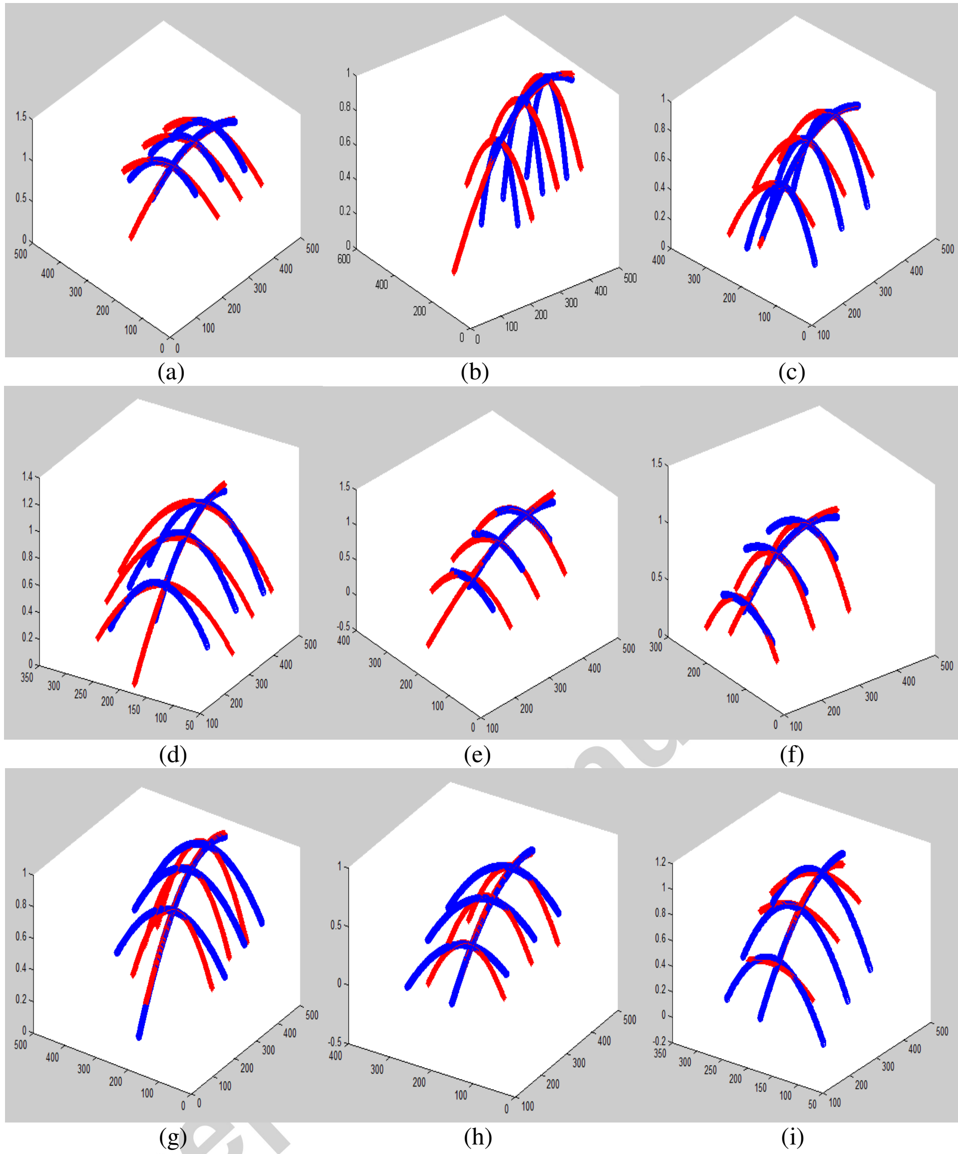


Fig. 7. Example of matching results of curve-skeletons from different genders and finger types. (a) Matching result of [(male, thumb)--(male, index finger)] in table I, (b) Matching result of [(male, thumb)--(male, little finger)] in table I, (c) Matching result of [(male, index finger)--(male, little finger)] in table I, (d) Matching result of [(female, thumb)--(female, index finger)] in table I, (e) Matching result of [(female, thumb)--(female, little finger)] in table I, (f) Matching result of [(female, index finger)--(female, little finger)] in table I, (g) Matching result of [(male, thumb)--(female, thumb)] in table I, (h) Matching result of [(male, index finger)--(female, index finger)] in table I, (i) Matching result of [(male, little finger)--(female, little finger)] in table I.

Fingerprint recognition experiment based on curve-skeletons is then implemented on our established database. Fig. 8 shows the Receiver Operating Characteristic Curves (ROCs) of different match score indexes. Their Equal Error Rate (EER) was obtained from 541 genuine scores and 292,140 imposter scores (generated from 541 fingers, 2 pictures of each finger).

From the results, we can see that an EER of around 15% can be obtained when matching 3D fingerprint curve-skeleton feature by simple ICP algorithm. The index of mean distance between matched pairs is better than the percentage of matched points. Curve-skeleton feature of 3D fingerprint image can be used to distinguish different fingers even though it is not as accurate as other higher level fingerprint features.

Since both 2D fingerprint features and 3D structural features are provided simultaneously by 3D fingerprint images, we aim to study whether improved performance can be achieved by combining 2D and 3D fingerprint features. For 2D fingerprint features, we selected minutiae due to their distinctiveness and popularity. It was extracted and matched by the method proposed in [25]. There are lots of miutiae-based fingerprint matching algorithms [1, 25, 31-38]. We selected the one proposed in Ref. [25] for the reason that it ranks 1st on DB3, the most difficult database in FVC2002 and outperforms the best two algorithms PA15 and PA 27 on four databases in FVC2002. The percentage of matched minutiae pairs was taken as the match score (MS_{2D}). Meanwhile, the curve-skeleton feature was chosen as the 3D structural fingerprint feature and mean distance between matched pairs was taken as the match score (MS_{3D}). A simple adaptive weighted sum rule is used to combine the 2D and 3D matching scores. The combined score can be expressed as:

$$MS_{2D+3D} = w / MS_{3D} + (1-w) \times MS_{2D} \quad w \in [0,1] \tag{2}$$

The weight w is adaptively tuned to provide the best verification results at step length of 0.01.

Fig. 9 shows the ROCs achieved by using minutiae and curve-skeleton separately, as well as their combination. It is notable that minutiae clearly outperforms curve-skeleton in terms of accuracy. However, the best result is achieved when combining minutiae and curve-skeleton feature where an EER of 3.4% is obtained. This experiment fully demonstrates that higher accuracy can be achieved if 3D fingerprint images are used compared with 2D fingerprint recognition.

TABLE I. EXAMPLES OF EXTRACTED CURVE-SKELETONS.

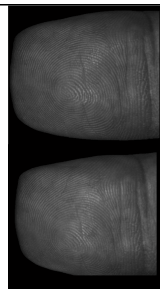
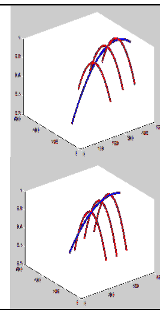
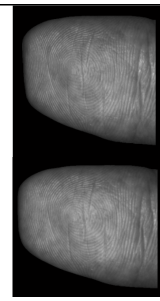
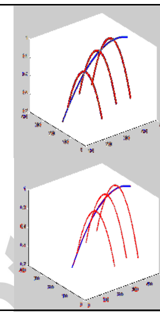
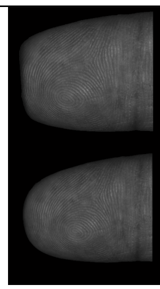
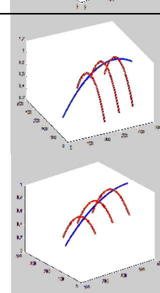
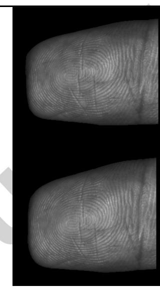
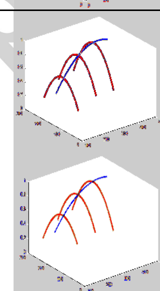
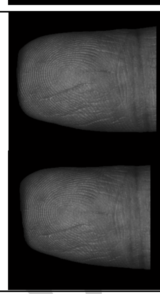
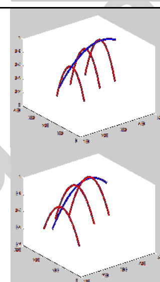
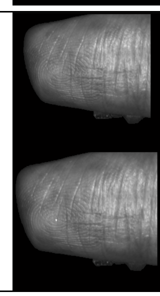
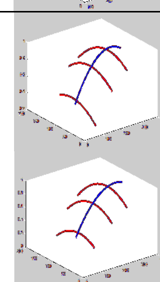
Finger Type \ **Gender**		**Male**		**Female**	
		Orignial 2D image	Curve-skeleton	Orignial 2D image	Curve-skeleton
Thumb	Session 1 (a1)				
	Session 2 (a2)				
Index Finger	Session 1 (b1)				
	Session 2 (b2)				
Little Finger	Session 1 (c1)				
	Session 2 (c2)				

TABLE II. MATCHING RESULTS BASED ON CURVE-SKELETONS.

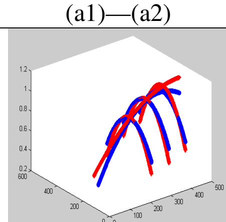
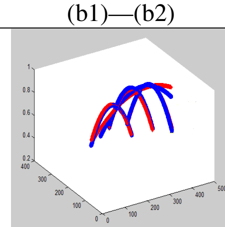
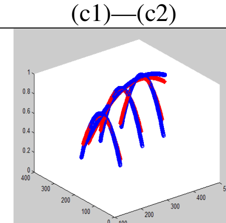
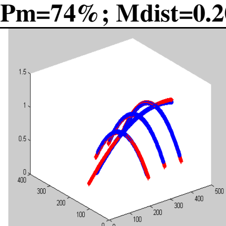
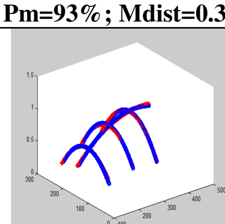
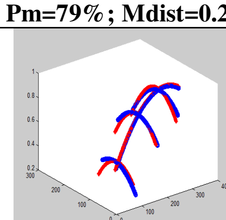
Finger Type \ **Gender**	**Thumb**	**Index Finger**	**Little Finger**
	(a1)—(a2)	(b1)—(b2)	(c1)—(c2)
Male			
	Pm=74%; Mdist=0.20	**Pm=93%; Mdist=0.39**	**Pm=79%; Mdist=0.25**
Female			
	Pm=94%; Mdist=0.72	**Pm=97%; Mdist=0.09**	**Pm=90%; Mdist=0.32**

TABLE III. MATCH SCORES CORRESPONDING TO FIG. 7.

Index \ Label	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)
Pm (%)	57	38	53	55	45	62	50	53	57
Mdist	8.3	13.7	2.9	6.8	14.8	3.1	4.0	4.1	4.6

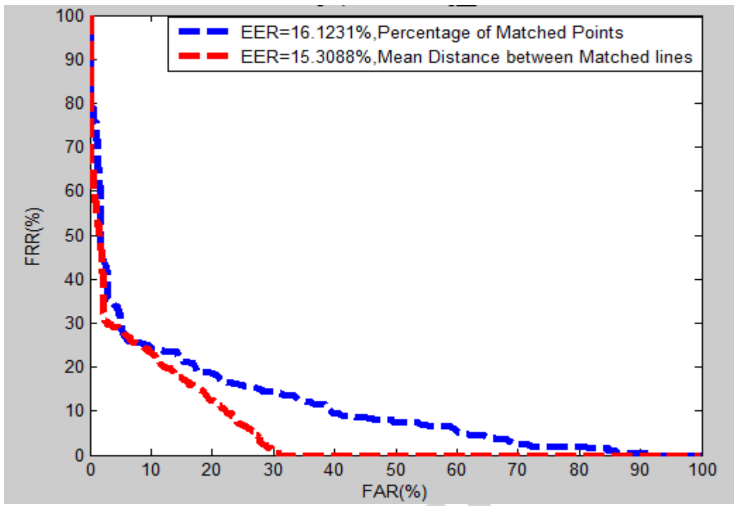


Fig. 8. ROCs with curve-skeleton feature.

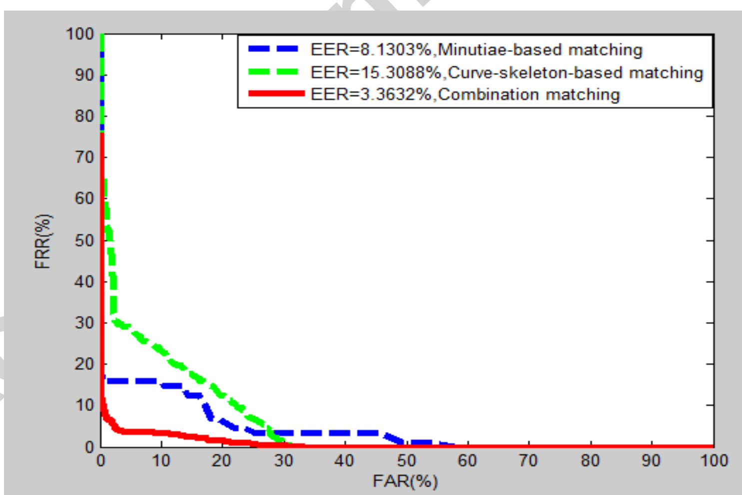
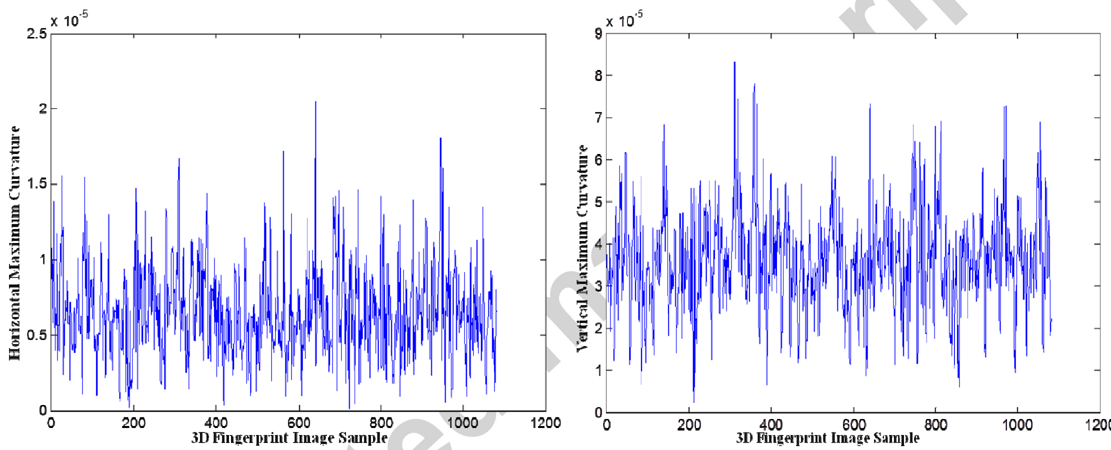


Fig. 9. ROCs with different fingerprint features.

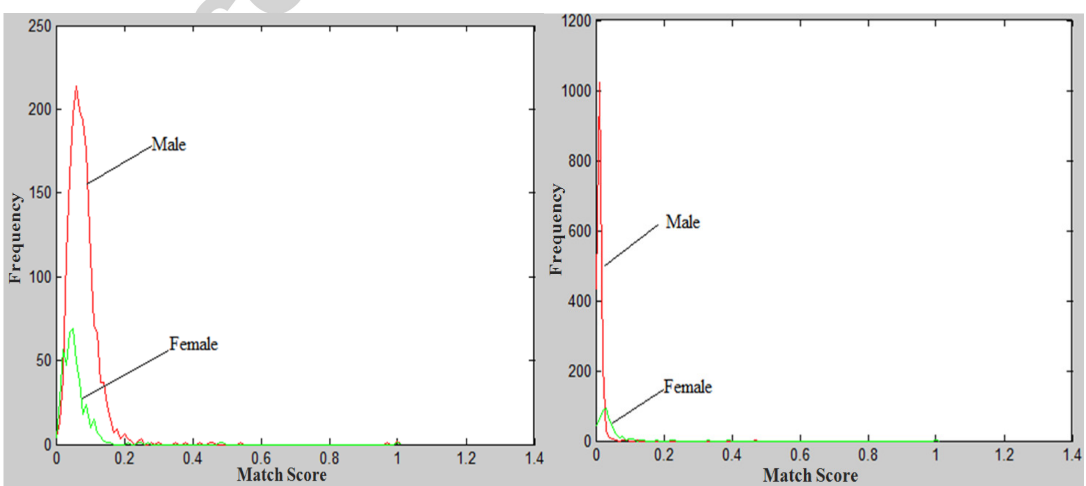
C. Case 2: Overall Maximum Curvatures based Gender Classification

Since our 3D fingerprint images are generated by reconstruction where binary quadratic function is taken as the finger shape model, two parameters are used to depict the overall finger shape curvature. Fig. 10 shows the values of maximal horizontal curvature feature and maximal vertical curvature feature in our database. We found both of these curvature features are very small. They cannot be used for personal authentication. Thanks to the composition of database of, different genders we investigated whether this feature is useful for gender classification. We then plot the distribution maps of norm curvature features separated by gender, as shown in Fig. 11. The ROCs are also shown in Fig. 11. From the figure, we found that the vertical maximum curvature can reach an EER of around 19%, while horizontal maximum curvature disabled to classify genders. It shows that there is little difference in the horizontal profile no matter male or female but the vertical profile is different.

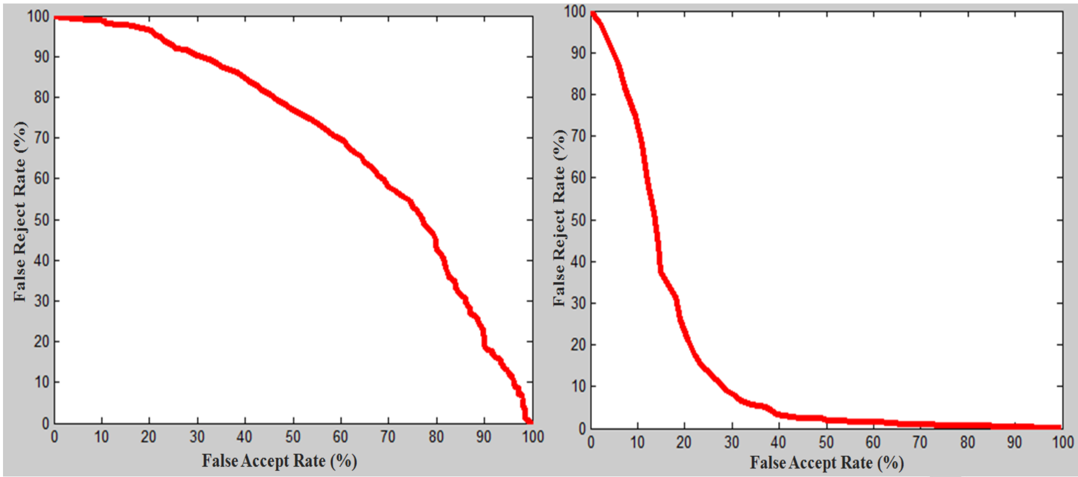


(a) (b)

Fig. 10. Values of overall maximum curvature. (a) Horizontal maximum curvature, (b) Vertical maximum curvature.



(a) (b)



(c) (d)

Fig. 11. Overall curvature features for gender classification. (a) Distribution map of horizontal maximum curvature, (b) Distribution map of vertical maximum curvature, (c) ROC curve of (a), (d) ROC curve of (b).

V. CONCLUSIONS AND FUTURE WORKS

This paper studied features on 3D fingerprint images and the possible applications of such features. Thanks to the availability of 3D fingerprint images, more features can be extracted. Fingerprint features that are coarser than Level 1 features — Curvature Fingerprint Features, were for the first time defined in this paper. Then, the possible applications of such features were investigated. Since such features are coarser than Level 1 feature, not high recognition accuracy (EER was ~15% when only 3D curve-skeleton was used for recognition) was achieved by barely using these features. However, an EER of 3.4% was realized by including Curvature Features into fingerprint recognition which demonstrates that this feature can be taken as an additional feature to assist fingerprint recognition. We also found that the proposed sectional maximum curvatures can be used for human gender classification. In this paper, simple feature extraction and matching algorithm were used. We believe that higher accuracy can be achieved if more advanced feature extraction and matching methods are proposed in the future. Discovering the relationship between different levels of fingerprint features and proposing more powerful fusion strategy will further improve 3D fingerprint recognition performance.

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