Hand Geometry Based Biometric Recognition

Abdulkadir Çelikkanat

May 31, 2016

1 Introduction

1.0.1 Problem Definition

The arising and impressively developing field, biometrics, has been continuously drawing attentions of new researches. The aim of biometrics is the automated identification of people based on their physiological and behavioral traits such as fingerprints, palm print, retina, hand geometry, speech and handwriting. Despite the biometric systems based on hand shape and geometry are considered as low/medium security systems, they have many advantages. It is more user friendly, low costly, low computational complexity, easy to obtain the hand images of people.

1.1 Related Works

The interest in hand geometry based recognition systems increases day by day, and it has gained significant development, since proposed in 1970s. However, the first hand recognition systems has required the usage of pegs which help to determine hand position as in the work of [5]. In the recent years, the systems is unconstrained and contactless hand geometry biometrics [2], [3], [1].

In other works, the hand geometry and other biometric traits are combined. For instance, the work of [7] proposed unified framework for hand verification, which extracts hand geometry (2D and 3D), palmprint (2D and 3D) and texture of the fingers using a 3D digitizer. The work of [6] combines hand geometry and palmprints.

In this paper, I will consider the hand geometry based biometric recognition system, test and compare the models proposed by [2], [1] over two different datasets

2 Datasets

In this paper, I have worked on two different datasets: IIT-Delhi Touchless and Bosphorus. The IIT Delhi dataset was collected by using a simple and touchless imaging setup. The resolution of these images is 800x600 pixels, and contains images of 235 users 4-6 images from each subject, from each of the left and right hand, in varying hand pose variations. The dataset is very challenging, because it is obtained by using a touchless imaging setup. (figure 2)

Figure 1: Samples from the IITD dataset

The bosphorus dataset is easier compared to IIT-Delhi. The dataset contains 642 subjects with 6 images/person, that is, three right-hand images and three left-hand images, but I have only used right hand images in the experiments throughout the paper. 160 among 918 subjects have hand images with time lapses of several months. The samples from the dataset is given in the figure **??**

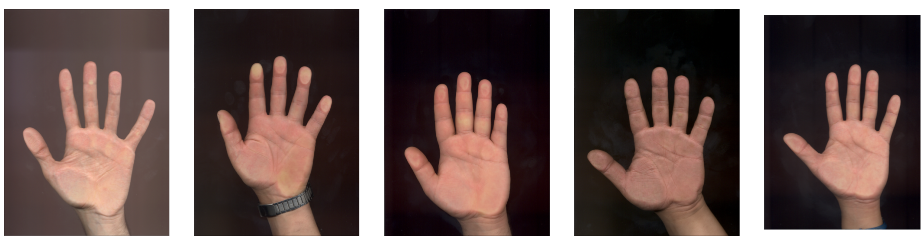


Figure 2: Samples from the IITD dataset

3 Explanation of the Proposed Approach

3.1 Hand Segmentation

The objective of hand segmentation is to detect hand region of the images. Despite the task seems relatively not so hard, it may be the most important task, because it has high influence on the success of subsequent processes. The artifacts due to the rings, wristwatch, or belts/chains make the segmentation harder. Further, the delineation of the hand contour must ve very accurate, since the small differences between hand contours can play significant role in recognition.

I have tested two different methods in order to extract hand region: morphological operations and skin detection. Since the hand images are rgb, I have tried to detect hand by skin detection algorithm, but it does not perform well. Hence, the morphological operation are applied to hand datasets.

For the Bosphorus dataset, firstly, images are converted into grayscale.

Figure 3: Better segmented images

To improve the contrast of the image, imadjust is applied. The grayscale image is converted into a binary image using a certain threshold value of 0.35. 2D median filter of size 5x5 is applied to get rid of possible noises. Dilation operation with a disk structuring element (SE) of size 3px followed the erosion operation with the same size SE. Since the IITD dataset is more challenging than Bosphorus, more operations are used for it.

Figure 4: Worser segmented images

Similarly, the Otsu's method are applied in order to binarize images. Then median filter of size 7px is used to remove noises. The erosion operator of structuring element (SE) size 7px, closing operator of size 11px, again closing of SE size 5px, erosion of SE size 3px, median filter of size 15px, closing operator of SE size 11px two times, and finally opening of SE size 5px are applied, respectively.

After segmentation of images, I have used bwboundaries() function of Matlab to extract the contours of the hands.

3.2 Hand Registration

The hand registration process contains the translation and rotation of the hand. Translation, and rotation of hands is required to put them in certain alignment, so possible error caused by hands' initial angles and positions can be minimized. The moments of a binary image is defined in [1] as

$$m_{i,j} = \sum_{(x,y)\in object} x^i y^i$$

and the centroid is

$$\hat{x} = \frac{m_{1,0}}{m_{0,0}}, \quad \hat{y} = \frac{m_{0,1}}{m_{0,0}}$$

Therefore, the central moments can be written as

$$\mu_{i,j} = \sum_{(x,y)\in object} (x-\hat{x})^i (y-\hat{y})^j$$

Then the orientation of the hand mask can be found with

$$\theta = 0.5 * tan^{-1}\left(\frac{2\mu_{1,1}}{\mu_{2,0}-\mu_{0,2}}\right)$$

he regionprops() function of Matlab returns also measurements with specified property.

Figure 5: Better rotated samples

Figure 6: Not good rotated samples

Finally, the hand orientation is finished by rotating the hand in such a way that the major axis of the hand becomes vertical. The hand is rotated by ϕ in counterclockwise direction

$$\phi = \begin{cases} 90-\theta & 90 \geq \theta \geq 0 \\ 90-\theta & -90 \leq \theta < 0 \end{cases}$$

The center of the hand mask are also shifted to the point (w*0.6, h*0.45) for each dataset where w and h denote the width and height of images. Since the size of images depends only on the dataset, the target point is the same for images in the same dataset. This process is especially done in order to reduce error in contour comparison in the method defined in [1].

3.3 Ring Artifact Removal

Due to the finger wearing rings may sometimes cause that finger and hand be seperated. Hence, if there exists an isolated finger, it should be detected, and

be connected to the hand region.
To detect an isolated finger, I have used the idea that the size of the isolated finger must be less than hand, and its center points must remain inside the region that hand's extreme points determine. After finding the isolated finger, it is rotated such that finger become vertical. Then it is extended by dilation operation with line structuring element having length 40 and angle 91 to attach the hand, and rotated to its original orientation. The bwpropfilt() function of Matlab is used to find the disconnected finger, which gives the extracts all connected components (objects) from a binary image.

(a) Initial Hand (b) Rotated (c) Extended (d) Connected

Figure 7: Pictures of animals

3.4 Extracting Hand Extremities

Detecting and localizing accurately the peaks and valleys of the fingers is important for further processes: feature extraction, finger and contour registrations. Initially, the curvature method is tested, which aims to find peaks, and valleys by looking curvature of the hand contour. However, it is sensitive to contour irregularities and it did not give successful results. Therefore, the method described in [4] is used later, and unfortunately, this method performed worser than the previous one. Finally, the technique used in [2], [1] is preferred.

The method firstly finds the point called as *reference*, which is on the boundary where the major axis line intersects, passing on the centroid of the hand. (figure 8) Since the wrist boundary are the least affected by rotation of hands, it is relatively more stable point. After finding the *reference point*, finger feature points are extracted by computing the euclidean distance map (figure 9a) between the reference point and the contour points. Then, the peak and valley points are found in the distance map, which correspond to the finger extremities, thumb, index, middle, ring and little fingers respectively.

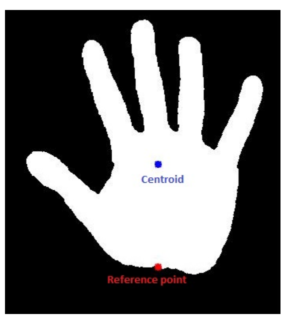
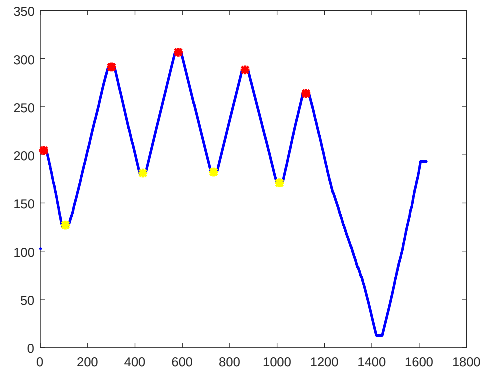
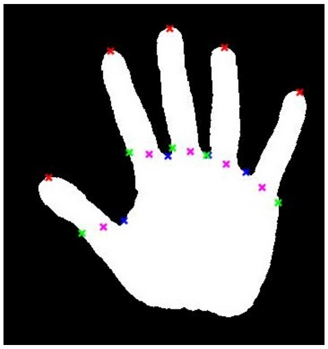


Figure 8: Reference Point



(a) Distance Map



(b) Finger Features

Figure 9: Pictures of animals

In order to complete to find the finger extremities, one more valley point is needed for the right side of the little finger. Let p_j denote peak points, v_j be valley points. The index Γ_{c_j} of composite valley c_j corresponding to the valley v_j is extracted using the indexes of p_j and v_j as,

$$\Gamma_{c_j} = \begin{cases} \Gamma_{p_j} - (\Gamma_{v_j} - \Gamma_{p_j}), & \Gamma_{p_j} < \Gamma_{v_j} \\ \Gamma_{p_j} + (\Gamma_{p_j} - \Gamma_{v_j}), & \Gamma_{p_j} > \Gamma_{v_j} \end{cases} \quad for\ j \in [1,5]$$

Finally, the middle points in the finger ends are defined as

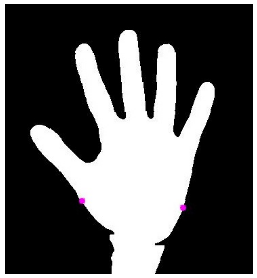
$$x_{m_j} = (x_{\Gamma_{v_j}} + x_{\Gamma_{c_j}})/2\ and$$
$$y_{m_j} = (y_{\Gamma_{v_j}} + y_{\Gamma_{c_j}})/2\ for\ j \in [1,5]$$

All points are depicted in the figure 9b, where red and blue colors are finger peaks and valleys, green points are composite and magenta points are mid-points.

3.5 Wrist Completion

The hand contours obtained after segmentation have irregularities in the wrist regions due to clothing or the difference in the angle of the forearm and the pressure. Hence, the hand is guillotined at the index points Γ_{u_1} and Γ_{u_5}.

$$\Gamma_{u_1} = \Gamma_{p_1} - (\Gamma_{p_1} - \Gamma_{c_1}) * 1.75\ and$$
$$\Gamma_{u_5} = \Gamma_{p_5} + (\Gamma_{p_5} - \Gamma_{c_5}) * 1.75$$



(a) Before guillotining

(b) Wrist Completion

Figure 10: Pictures of animals

3.6 Finger Registration

Since the images in the dataset were obtained in the peg-free environments, it is important to register fingers to increase the recognition accuracy of the system. The alignment of the fingers are done as follows:
Let w_j be the orientation of the jth finger after registration with respect to the vertical axis in counterclockwise direction. The angle ϕ_i of a finger i can be obtained with

$$\phi_i = tan^{-1}\frac{y_{p_i} - y_{m_i}}{x_{p_i} - x_{m_i}}$$

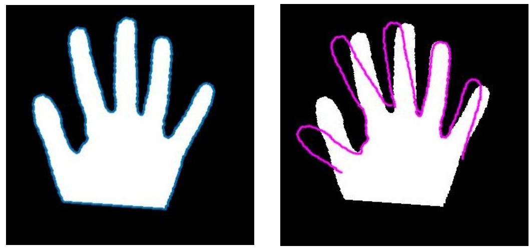
where y_{p_i}, x_{p_i}, y_{m_i} and x_{m_i} are peak and mid-points of finger i. The new coordinates of the ith finger can be obtained by

$$x_{i_{new}} = x_{m_i} + (x_{o_i} - x_{m_i}) * cos\phi_i - (y_{o_i} - y_{m_i}) * sin\phi_i$$
$$y_{i_{new}} = y_{m_i} + (x_{o_i} - x_{m_i}) * sin\phi_i - (y_{o_i} - y_{m_i}) * cos\phi_i$$

where x_{o_i}, and y_{o_i} are the present coordinates of finger i.
The values of w_i's are considered as given in the table **??**

	j=1	j=2	j=3	j=4	j=5
w_j	60	30	10	-10	-20

Table 1: The angles of fingers after finger registration



(a) Inital Contour (b) After registering

Figure 11: Finger Registration

3.7 Feature Extraction and Results

3.7.1 Geometrical Feature Extraction

By using the finger feature points, the geometrical distances are defined in [2] as

$$d_j = \begin{cases} \sqrt{(x_{p_j} - x_{m_j})^2 + (y_{p_j} - y_{m_j})^2} & j \in [1,5] \\ \sqrt{(x_{p_2} - x_{m_1})^2 + (y_{p_2} - y_{m_1})^2} & j = 6 \\ \sqrt{(x_{p_5} - x_{m_2})^2 + (y_{p_5} - y_{m_2})^2} & j = 7 \end{cases}$$

If n number of distances are used, then the dimension of final geometrical feature is n*(n-1)/2. The geometrical feature description g(n*(n-1)/2) is the ratios of $\frac{d_i}{d_j}$ where $i < j$ and $i, j \leq n$.

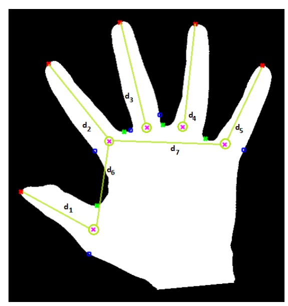


Figure 12: Geometric features

3.7.2 Distance and Orientation Maps

The distance map $d\mu(i)$ is defined over updated hand contours in finger registration process with reference point in the following way

$$d\mu(i) = \sqrt{(x_r - x_i)^2 + (y_r - y_i)^2}$$

where (x_r, y_r) is the coordinate of the reference point, and (x_i, y_i) is the *ith* pixel of hand contour.
Similarly, the orientation map $o\mu(i)$ is defined as

$$o\mu(i) = 90 + tan^{-1}\left(\frac{y_r - y_i}{x_r - x_i + \sigma}\right)$$

where σ is a very small number.

Since dimensions of $d\mu(i)$ and $o\mu(i)$ depend on the scale of the image, size of image contours may be different. To transform the higher dimension feature into low dimension feature vector and to choose the most discriminative features, the 1-D wavelet decomposition at level 5 using Daubechies-1 decomposition over $d\mu(i)$ and $o\mu(i)$. Then the first 50 coefficients of the wavelet decomposition is used. The wavelet toolbox of Matlab is used for decomposition.

3.8 Hand Contour Based Comparison

In the work of Erdem Yoruk et al [1] used a method which based on Hausdorff distance measure between the contours to discriminate hands. In order to compare different hand geometries, the Hausdorff distance is an effective method since the distance measures proximity rather than exact superposition so it is more tolerant to perturbations in the locations of points. The Hausdorff distance is defined as

$$H(F,G) = max(h(F,G), h(G,F))$$

where

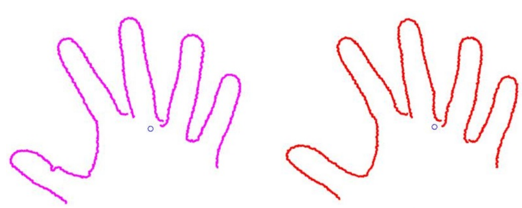
$$h(F,G) = \max_{f \in F} \min_{g \in G} \parallel f - g \parallel$$

and where $\{f_i\}$ and $\{g_i\}$ denote contour pixels of two hands. However, they used a modified Hausdorff distance measure defined as

$$h(F,G) = \frac{1}{N_f} \sum_{f \in F} \min_{g \in G} \parallel f - g \parallel$$

$$h(G,F) = \frac{1}{N_g} \sum_{g \in G} \min_{f \in F} \parallel f - g \parallel$$

N_f and N_g are the numbers of points in the sets F and G.



(a) Contour Sample I (b) Contour Sample II

Figure 13: Comparison of different contours

They discounted the wrist region by attaching a low weight since there resides still some uncertainty adversely affecting correct recognition. Similarly, I did not take the wrist region in comparison of hands, and choose the norm as euclidean in the Hausdorff distance formula.

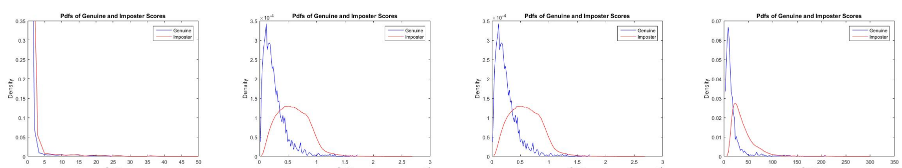
4 Experimentation results

I have performed experiments on two different datasets: IIT Delhi and Bosphorus, and compared my scores with the work in [2] and [1]. In experiments, I have only used the right hand images in the sets, and unfortunately some images causes my implementation to give error, so those samples are thrown out; 24 images for IIT Delhi, and 21 images for Bosphorus.

The scores of my experiment over the IITD dataset seem better than the work [2] for geometric, distance and orientation features. However, the fusion of three scores did not make contribution much for my experiment, their EER score decreased up to 0.52 while my score remained about 22.158 for min-max normalization.

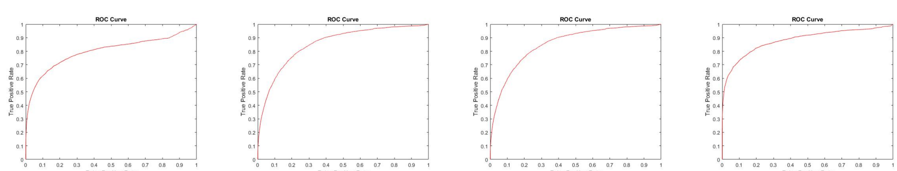
Table 2: My caption

EER for IITD dataset							
	g(6)	g(10)	g(21)	'd'	'o'	fused	contour
My score	31.4014	30.7347	25.1195	21.9936	21.9973	22.1580 (min-max)	18.7350
S.Sharma et al			38.46	26.83	34.06	0.52	



(a) Geometric g21 (b) Distance map (c) Orientation map (d) Contour

Figure 14: Pdfs of Genuine and Imposter Scores for IITD dataset



(a) Geometric g21 (b) Distance map (c) Orientation map (d) Contour

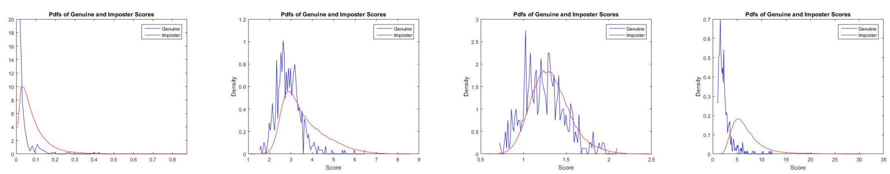
Figure 15: ROC Figures for IITD dataset

Since the private dataset used in [2] were obtained by using scanner, it looks the Bosphorus dataset. Hence, I have also compared my scores over Bosphorus dataset with the scores of S. Sherma over JUET dataset. 3.

Table 3: My caption

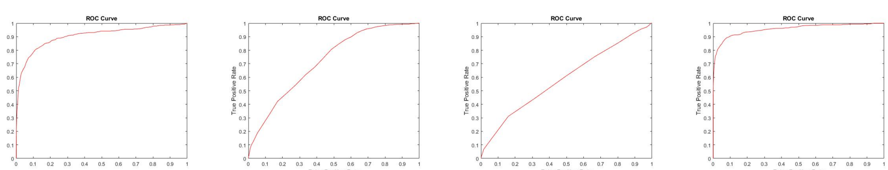
EER for Bosphorus dataset							
	g(6)	g(10)	g(21)	’d’	’o’	fused	contour
My score	24.5751	19.7363	15.8795	36.2267	45.0265	16.6858 (min-max)	10.0063
EER for private JUET dataset							
S.Sharma et al	23.60	22.40	21.80	17.80	0.208	0.4 (min-max)	

My score over Bosphorus dataset is close the scores of S. Sherma over JUET dataset except orientation and fusion values. Again, the fusion has made enormous contribution for their system, but my fused system did not work well.



(a) Geometric g21 (b) Distance map (c) Orientation map (d) Contour

Figure 16: Pdfs of Genuine and Imposter Scores for Bosphorus dataset



(a) Geometric g21 (b) Distance map (c) Orientation map (d) Contour

Figure 17: ROC Figures for Bosphorus dataset

In the work of Erdem Y [1]. et al, they analyzed correct identification accuracy for their system by changing the training set size, and enrollment set size for contour features. Similar to their work, I have also compared my experiments with their scores in **??** and **??**.

Correct Identification Percentage (Double Training Set)					
Set size	20	35	50	100	All (193/458)
My scores	81.665.77	80.005.71	84.005.29	80.662.08	79.621.82
Erdem Y. et al	98.75	98.14	97.97	97.21	93.51

Table 4: Correct Identification percentage for a training Set containing 2 images for each person

Correct Identification Percentage (Single Training Set)					
Set size	20	35	50	100	All (193/458)
My scores	40.839.17	40.008.28	42.008.76	40.334.32	39.8110.41
Erdem Y. et al	2.67	3.23	4.23	4.38	3.61

Table 5: Correct Identification percentage for a training Set containing only 1 image for each person

My system has showed much better performance for a training set containing only one image for a person with respect to the work of Erdem Y [1]. This also may depend on the size of the dataset, since I have only used right hand images. My system accuracy increased up to around 80% for a training set containing two images for each person. The size of the enrollment set does not affect my system much similar to the work of Erdem Y [1].

Correct Identification Percentage (Single Training Set)					
Method name	g(6)	g(10)	g(21)	distance	orientation
My score	15.721.81	24.011.65	45.252.99	1.720.299	1.380.299

Table 6: Correct Identification Percentage (Single Training Set)

4.1 Conclusion

In this project, I have compared the two models described in [2] and [1] over two datasets. The model defined by Erdem Y [1] has perfomed better on two datasets. It is observed that the acquisiton method of dataset has great influence on the accuracy.

References

[1] Yoruk, E., Konukoglu, E., Sankur, B., & Darbon, J. (2006). *Shape-based hand recognition*. IEEE Transactions on Image Processing, 15(7), 18031815.

[2] Shefali Sharma, Shiv Ram Dubey, Satish Kumar Singh, Rajiv Saxena, Rajat Kumar Singh *Identity verification using shape and geometry of human hands*, Expert Systems with Applications 42 (2015) 821832

[3] Mrcia V. P. do Nascimento, Leonardo V. Batista, N. L. Cavalcanti, Jr. *A new approach to biometric recognition based on hand geometry* Proceeding, SAC '15 Proceedings of the 30th Annual ACM Symposium on Applied Computing, Pages 59-65

[4] Irfan Ahmad, Zahoor Jan, Inayat Ali Shah, Jamil Ahmad *Hand Recognition Using Palm and Hand Geometry Features*, Sci.Int.(Lahore), 27(2), 1177-1181, 2015

[5] Sanchez-Reillo, R., Sanchez-Avila, C., and Gonzalez-Marcos, *A. Biometric identification through hand geometry measurements.* IEEE Transactions on Pattern Analysis and Machine Intelligence, 22, 10 (Oct 2000), 1168 - 1171.

[6] A.Kumar ,D.Zhang *Personal recognition using hand shape and texture* IEEE Transactions On Image Processing ,Vol .15 ,No.8,August.

[7] Kanhangad, V., Kumar, A., and Zhang, D. *A unified framework for contactless hand verification.* IEEE Transactions on Information Forensics and Security, 6, 3