# **Person Identification Prototype Using Hand Geometry**

Abdelhamid Abdesselam<sup>1</sup> and Ameera Al-Busaidi<sup>2</sup> Department of Computer Science, College of Science Sultan Qaboos University P.O. Box 36, Al-Khoudh 123,Muscat, Oman <u>ahamid@squ.edu.om</u><sup>1</sup>-and ameera.albusaidi@gmail.com<sup>2</sup>

### Abstract

This paper describes our recent research work on hand-based person identification. The main focus is on the use of geometrical characteristics of the hand in the identification process.

Several state-of-the-art person identification methods using hand geometry were reviewed and the most commonly used geometrical features were identified; a recent research work [1] that has included most of these features was selected for implementation and evaluation. We have also tested some new geometrical features and evaluated their impact on the accuracy rate of the identification system.

A set of experiments was conducted on a hand image database provided by Bogazici University, in Turkey (Bosphorus database). The results of these experiments demonstrated that the identification system based on the set of features proposed by Prasad et al is of high recognition rate, and allowed us to identify a new geometrical feature that further improve this rate.

## 1. Introduction

During the last few decades several methods were proposed for hand-based person identification. Most of these methods use either hand geometry or hand palm-print and few others use both features. This paper describes and evaluate a person identification method we have proposed and implemented. This method is based on the geometrical features of the user's hand.

Hand geometry (sometimes referred to as hand shape) is a biometric that identifies individuals by the shape of the hand silhouette. It consists of measurements taken on various hand parts (mainly, fingers and hand palm). Finger lengths and widths are included in almost all published research works related to hand geometry ([2], [3]). Aspect ratios involving lengths and widths of the fingers and hand palm are also widely used. These measurements have the property of being invariant to changes in scale (due to zooming or change in camera-to-hand distance). Some research works ([4]; [5]) have reported the use of hand thickness (finger and palm thickness) to characterize person's hand

These measurements are usually based on distances between prominent landmarks, identified on the individual's hand (such as fingertips, valleys between fingers, etc.) [5].

Some recent research works included measurements that characterize the overall shape of the hand. Perimeter, eccentricity, convex area, extent, and solidity are some of these global measurements ([1], [6])

Although many papers have used the same geometrical features, they have adopted different approaches to measure them. Three major factors affect the performance of a geometry-based hand identification method:

a) The set of geometrical features used for hand representation: this set should be well selected and of sufficient number to be able to distinguish between different individuals.

- b) The accuracy with which the landmarks (key-points) are located: inaccurate location of key-points may lead to erroneous feature extraction which affects the accuracy of the whole identification system
- c) The complexity of the methods used for calculating the geometrical features and for performing the matching: efficient feature extraction algorithms as well as fast matching techniques are needed to develop reasonably fast biometric systems.

# 2. The General Framework for the Proposed Method

Like any other access control system, the proposed prototype works in two modes: enrolment and deployment modes. Any user of the system should first register through the enrolment mode, where the system captures a defined number of hand images from which geometrical features are extracted and stored in the system database. Whenever a user tries to access the system, the deployment mode is activated. In this mode the system acquires one hand image, extracts geometrical features and compares them to the stored features in the database to decide on the identity of the user.

The two modes share four major modules, Image Acquisition, Binarization, Image Rotation and Feature Extraction. Extracted features are stored in a normalized 1-D vector called geometrical feature vector. In the matching and Decision Making module, the feature vector extracted during the deployment mode is compared against the feature vectors in the database to decide about the identity of the user or declare him/her as imposter. The schematic diagram of the system is shown in Figure.1

## 3. Some Implementation Details

## 3.1. Image Acquisition:

Captured images are converted to gray scale images and resized to have a predefined number of rows and columns.

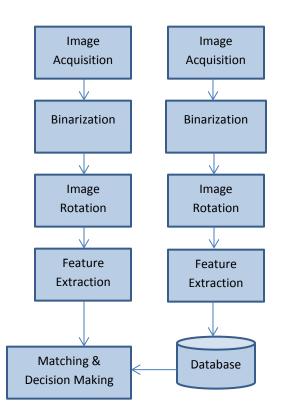


Figure 1. The schematic diagram of the system

## 3.2. Binarization:

In the binarization module, the hand is isolated from the background. The gray-scale hand image G is converted to a black and white image B using the well-known Otsu's algorithm [7].

## 3.3. Image Rotation:

The binarized image B is rotated by an angle  $\theta$  where  $\theta$  is estimated by the rotation angle of the major axis of the best fitting ellipse for the hand region relative to the column axis OY. See Figure 2.

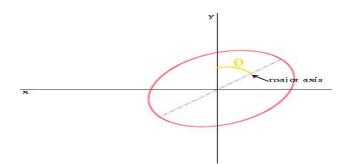


Figure 2. Rotation angle  $\theta$  can be estimated based on the orientation of the best fitting ellipse.

The formula for calculating this angle is given below [1].

$$\theta = \begin{cases} \tan^{-1} \left( \frac{l_{11} - l_{22} + \sqrt{(l_{11} - l_{22})^2 + 4l_{12}^2}}{-2l_{12}} \right) & \text{if } l_{11} > l_{22} \\ \\ \tan^{-1} \left( \frac{-2l_{12}}{l_{22} - l_{11} + \sqrt{(l_{22} - l_{11})^2 + 4l_{12}^2}} \right) & \text{otherwise} \end{cases}$$

Where  $l_{11}$ ,  $l_{12}$ ,  $l_{22}$  are the normalized secondorder moments of pixels in the binarized image B and are given by

$$l_{11} = \frac{\sum_{(x,y)\in P} (y - c_y)^2 B(x,y)}{\sum_{(x,y)\in P} B(x,y)}$$

$$l_{22} = \frac{\sum_{(x,y)\in P} (x - c_x)^2 B(x,y)}{\sum_{(x,y)\in P} B(x,y)}$$

$$l_{12} = \frac{\sum_{(x,y)\in P} (x - c_x)(y - c_y) B(x,y)}{\sum_{(x,y)\in P} B(x,y)}$$

(cx, cy) denotes the location of B's centroid and B(x, y) represents pixel value of B. P is the hand region.

The boundary pixels of the hand are extracted using a classical boundary tracking algorithm.

#### 3.4. Features Extraction

Hand geometrical features can be categorized as: shape features and pure geometrical features [1]

#### 3.4.1. Hand Shape Features

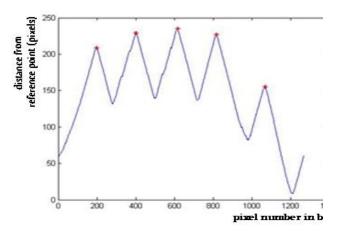
The shape of the hand is described using five measurements obtained from the binary image. These measurements are the hand perimeter, the extent of the hand region which is defined as the area of the hand region divided by the area of the bounding box, the eccentricity of the hand region which is defined as the ratio of the distance between the foci of the best fitting ellipse and its major axis length, the area of the convex hull of the hand region and the solidity of the hand region which is defined as the hand area divided by the convex hull area.

#### 3.4.2. Pure Geometrical Features

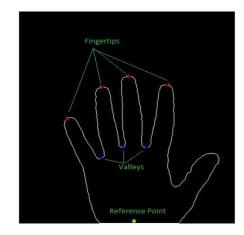
In their recent research work, Prasad et al adopted geometrical have 25 [1] measurements involving finger lengths and widths and some aspect ratios. The list of measurements includes the 4 finger lengths, 8 finger widths, 3 finger length ratios (ratios of the Middle finger to the Little, Index and Ring fingers respectively), 4 finger areas, 3 distances from finger valleys to the center of the hand region, the centroid of the palm and its width. A close look at the proposed features revealed that two important hand characteristics are not present in the list. These are the size of the palm region and the relative size of the fingers to the palm region. We have also noticed, during the experimentation phase, that two of the measurements included in the list, the coordinates of the centroid of the palm, vary significantly within the hand images of the same person, which might indicate that the centroid location is not a strong discriminative feature. For these reasons we have decided to include these two geometrical features and discard the centroid

from the list of features and evaluate experimentally the impact of these modifications on the system performance.

A three-step approach is devised to extract the geometrical features. First, a distance profile of the hand is generated. The main key points in the hand (fingertips and valleys) are then identified from the profile. The key points are used to estimate the geometrical measurements that characterize the hand. See Figure.3.



a)- Distance profile: distances from the reference point to all the boundary points on the hand



b)- Corresponding key points.

**Figure.3:** Detection of the fingertips(local maxima) & valleys (local minima) using distance profile

The distance profile records the distances from a reference point on the hand to the boundary pixels of the hand region. The bottom mid-point of the hand boundary is chosen as the reference point.

The local maxima and minima in the distance profile graph are used to approximate the location of finger tips and valleys, respectively.

Figure.4 illustrates the geometrical features that have been considered.

## 3.5. Matching and Decision Making

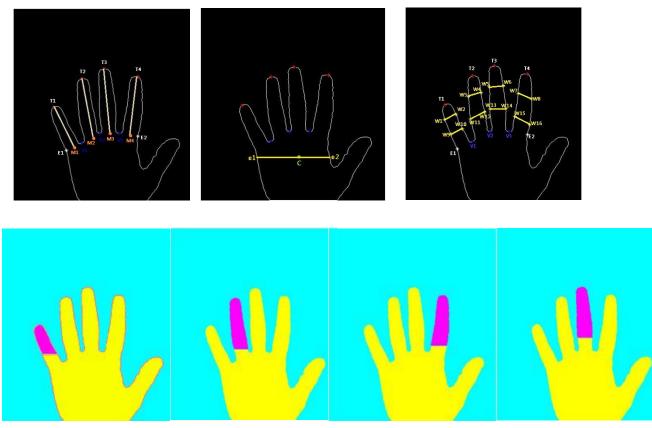
As mentioned earlier, a predefined number of images is captured in the enrolment phase. A three-step algorithm is then applied to each image in order to derive the geometrical feature vector associated to the image. The feature vectors are then normalized by applying the min-max normalization formula to each element (measurement) in the feature vector as shown below.

$$F = \frac{f - f_{min}}{f_{max} - f_{min}};$$

where f and F are the original and the normalized measurements, respectively,  $f_{max}$ , and  $f_{min}$  are the maximum and minimum values for f in the database

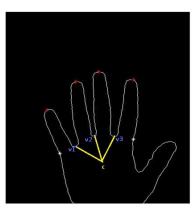
Normalized vectors are then stored in the database together with the identity of respective individuals.

The decision about the identity of a user is based on a predefined threshold and the well-known nearest neighbor classifier. The Euclidian distances between the normalized feature vector of the image taken at the deployment phase with all normalized feature vectors in the database are first calculated and the identity of the feature vector with the smallest distance is identified. If this distance is smaller than a pre-defined threshold the user is assigned the identified identity otherwise he/she is assumed to be an imposter



a)-Major features originally proposed by Prasad et. al





b)- The two Added features

Figure.4: Illustration showing the geometrical features considered in this work

## 4. Experimental results and discussion

## 4.1. Testing Dataset

The performance of the proposed system is evaluated on a public database (Bosphorus Hand database) provided by Bogazici University [8]. Images are acquired by a commercial scanner. There has no guiding pegs but the fingers are apart from each other. Among the 4846 images contained in the database, we selected the ones that do not include any accessories in the fingers or with arm. We ended 258 images representing 86 persons (3 images per person). Figure.5 shows a sample hand images from the Bosphorus databases.

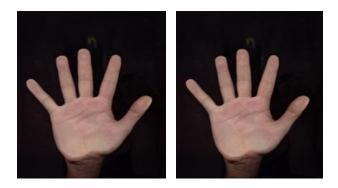


Figure 5. Hand images from the Bosphorus Database

# 4.2. Experiments

We have conducted three experiments; the first two aim at evaluating the performance of the system based on the geometrical features proposed by Prasad et al. The third aims at assessing the impact of the newly proposed features on the performance of the system.

The performance of a biometric system is usually measured by reporting its False Acceptance Rate (FAR) and False Rejection Rate (FRR) at various threshold values.

By plotting both FAR and FRR against different threshold values, we obtain the ROC graph. The Equal Error Rate (EER), that reflects the rate where both FAR and FRR are equal is usually used as a performance indicator of the system. Sometimes the accuracy rate (100-EER) is reported instead.

# 4.2.1. Experiment #1 & #2:

In the first experiment, two images were used for training and the third one for testing. The ROC graph for this experiment (Figure.6-a) shows an accuracy of 96% (EER is equal to 4%). In the second experiment, we have switched the testing and training images, the ROC graph for this experiment (Figure.6-b) shows an accuracy of 94.8% (EER is equal to 5.2%). This slight change in the accuracy is probably due to the fact that in the second experiment we have used only one hand image for training instead of two in the first experiment. But the error is still within the state of the artlevel.

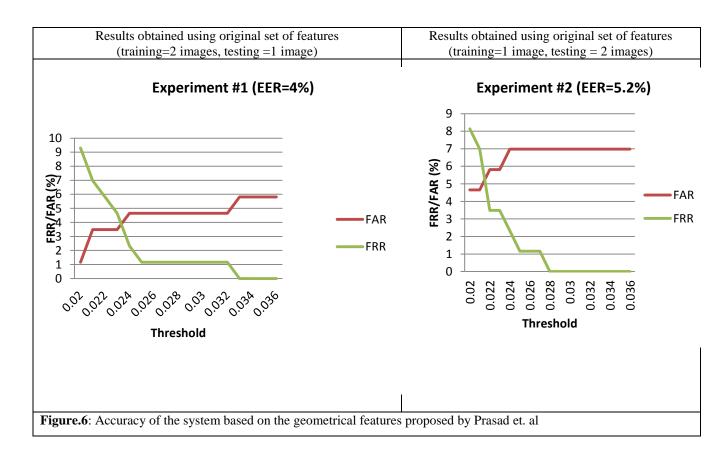
# **4.2.2.** Experiment #3:

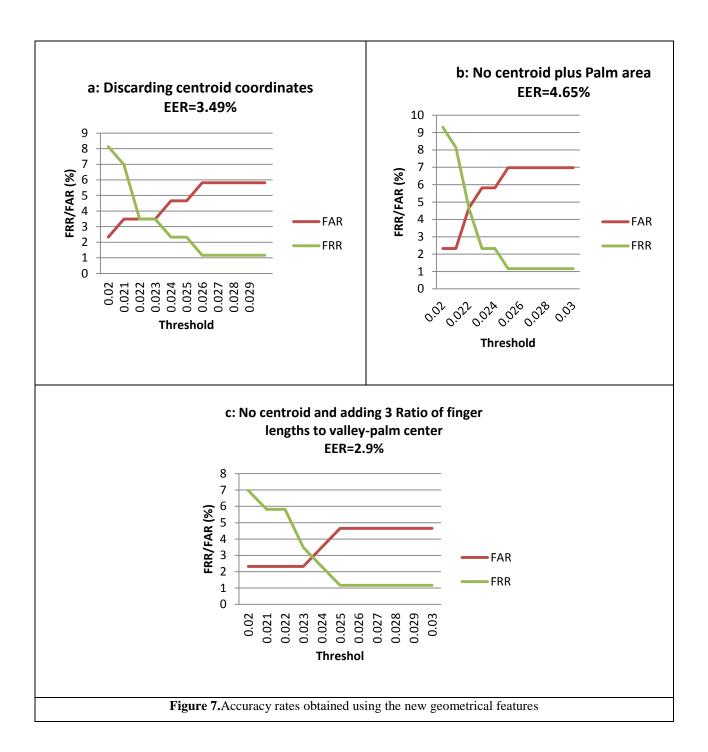
This experiment is conducted to test the effectiveness of the modified list of geometrical features we have suggested. This experiment was conducted on the original dataset (i.e. 2 images for training and 1 image for testing). Table.1 and Figure.7 summarize the results we have obtained. We can see that a slight improvement (from 96 % to 96.51%) was obtained just by discarding the centroid from the list of features. As mentioned earlier, the idea of discarding this feature came from our observation that the centroid coordinates change significantly in different images of the same user. We can see also that as expected, adding the ratios of finger lengths to valley-palm center distances have further improved the accuracy of the method (from 96.51% to 97.10%). In the other hand, we can notice that the other geometrical feature we have suggested (i.e. the area of palm region), did not improve the accuracy of the

system, actually it has worsened it from 96% to 95.35%. This is probably due to the fact the size of the palm is already represented by the width of the palm. Therefore this feature is redundant

Feature	Number of measurements	Accuracy
Original set	30	96%
Original set without centroid coordinates	28	96.51
Original set without centroid plus palm area	29	95.35
Original set without centroid plus 3 ratios finger lengths / distance valley to palm center	31	97.10

 Table.1: Accuracy obtained with various suggested sets of geometrical features





## 5. Conclusion

This paper reports the results of a biometric research work we have recently conducted. It consists of implementing , evaluating and improving a state-of-the-art hand-based identification system described in [1]. The system was successfully implemented and a new list of geometric features that improves the accuracy of the original work was identified. As a continuation to this research work, we have started addressing two issues:

- 1. Identify and apply a systematic approach for feature selection
- 2. Investigate the use of palmprint features together with geometrical ones.

#### 1. References

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