Personal Verification from the Geometry of Human Hands

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1. Introduction

Biometrics offers natural and scientific solution to key aspects of security management problems. Due to the increased security concerns in the past decade, biometrics has seen enormous growth and has found widespread applications in our everyday life. Widely researched biometrics traits include face, iris, fingerprint, hand geometry, palmprint, voice and signature. Of these, face and hand geometry biometric traits enjoy high user acceptance as these characteristics can be measured in a non intrusive manner, causing very little inconvenience to the user.

Hand geometry, along with the fingerprint and palmprint, is one of the hand based biometric modalities. Hand geometry based biometric systems exploit various features extracted from hand images to perform personal authentication. Due to limited discriminatory power of these features, hand geometry systems are rarely employed for applications that require performing identity recognition from a large scale database or applications where the highest level of security is desired. Nevertheless, these systems have gained immense popularity and public acceptance as evident from their extensive deployment for applications in access control, time and attendance applications and several other verification tasks. Major advantages of hand geometry systems include simple imaging requirements (features can be extracted from low resolution hand images), ability to operate under harsh environmental conditions (immune to dirt on the hand and other external factors), and low data storage requirements. In addition, hand geometry acquisition and verification is extremely fast. These distinct advantages over other biometrics helped the hand geometry systems capture a niche market.

History of hand geometry biometric technology/systems dates back over three decades. The hand geometry system *Identimat*, developed by *Identimation* in 70's, was one of the earliest reported implementations of a biometric system for commercial applications. Since then, the hand geometry biometric systems have found applications in wide variety of fields ranging from airports to nuclear power plants [15]. The hand geometry systems have traditionally enjoyed a market share of about 10 percent and have been quite popular for medium size verification applications. The *Recognition Systems* [26] offers range of time and attendance, and access control solutions based on hand geometry biometrics. Their access control solution named *HandKey* extracts over 90 measurements from the user's hand image and stores the information into a 9 byte template. *VeryFast* access control terminal, manufactured by *BioMet* partners [27], captures the image of user's two fingers. Features extracted by processing this image are encrypted and stored as a 20 byte template. *Accu-Time Systems* [28] also manufactures a similar access control device based on user's finger geometry. Several units of the above mentioned systems have been installed at various places around the world. The *INSPASS* is the first and the largest biometric verification program undertaken by the US government. The *HandKey* scanners were installed at certain airports in the US to accelerate the process of immigration for frequent fliers. Another large scale deployment was at 1996 Olympics Games, where hand geometry scanners were installed to restrict access to the Olympic Village.

Despite the commercial development and success of the hand geometry technology, there was not much literature available in the public domain until late nineties. However, since as early as 1970, several U.S. patents have been issued for personal identification devices based on hand/finger geometry measurements [21], [22], [20], [19]. Table 1 summarizes the inventions described in these patents. Most of the early work in the hand geometry literature was based on 2D images (intensity and color) of the human hand. However, with advancements in range image acquisition technology, a few researchers have also explored the utility of features extracted from range images of the hand. In the following sections, we describe in detail various methodologies proposed in the literature for 2D as well as 3D hand geometry biometrics.

Table 1: Summary of inventions on hand/finger geometry identification systems

Patent	Invention
[21]	Mechanical device (using bars and springs) to measure length and width measurements of the hand, placed palm down on a flat surface
[20]	Mechanical contact members are employed to measure outer dimension of fingers, while photoelectrical sensing devices compare the measurements with the ones stored in an identity card
[22]	Optical scanning device to measure finger lengths of four fingers (thumb not considered). Optical sensors are embedded on the flat surface to sense measurements, with a light source on top
[19]	Device captures virtual 3D image of the hand using a mirror to reflect the side view. Flat surface has four pegs with an illumination source on top. Various measurements including finger lengths/widths, hand thickness, surface area and perimeter are computed

2. 2D Hand Geometry

2D hand geometry technology is based on the features extracted from two dimensional image of the human hand. Major processing modules in a 2D hand geometry system are: Image acquisition system, preprocessing and feature extraction, feature matching and decision making. Following sections provide a detailed discussion on various approaches available for these processing tasks.

2.1. Imaging techniques

A typical imaging set up for a two dimensional hand geometry system would involve the following components: A CCD camera, illumination source and a flat surface. CCD camera employed is usually low to medium resolution as the hand geometry features can be extracted from binary images of the hand. Joshi et al. [16] are one of the earliest researchers to build a prototype hand based biometric system. Their system mainly comprised a CCD camera for imaging finger creases and a fluorescent tube for illumination. In order to minimize variations in imaging and subsequent performance deterioration, the placement of the fingers was constrained using a metal strip and a micro-switch, which also activates the frame grabber to capture images of the fingers. Another prototype hand geometry system developed by Jain et al. [2] employs image acquisition module that includes a camera, an illumination source and a flat surface with five pegs (similar to the one in patent [19]). A mirror was employed to project the lateral view of the hand on to the CCD. This enables the system to acquire top and lateral view of the user's hand in a single image of 640 × 480 resolution. The hand geometry system developed by Sanchez-Reillo et al. [1] employs an image acquisition module similar to the one in [3]. Pegs in their system, however, are equipped with pressure sensors to trigger the camera when a hand is detected on the platform.

Most of the early works in the literature employ pegs (on the flat surface where the user is required to place his/her hand) to restrict the position and movement of the hand during image acquisition. Though use of such constraints helps avoid registration/alignment of hand images before feature extraction, such systems cause inconvenience to the user and therefore are less user friendly. For example, elderly or people with arthritis and other conditions that limit dexterity may have difficulty placing their hand on a surface guided by pegs. Hence, a lot of researchers have focused their efforts to eliminate the use of pegs. Kumar et al. [4] employed a peg free imaging set up to acquire hand images. Users were requested to place their hand on the imaging table, with a digital camera mounted on top. They did not employ any special illumination, as the images were acquired in a well lit indoor environment. Authors in [14] employ an image acquisition system that includes a flat surface (for hand placement) with a VGA resolution CCD camera mounted on top. A uniform illumination is provided underneath the flat surface. Such an arrangement helps to acquire high contrast hand images which can binarized by simple thresholding. A few researchers [18], [12] have even used low resolution digital scanners to acquired hand images in a peg free manner. Though the above approaches do not use pegs to constrain hand placement, they require the user to place his/her hand on a flat surface. Such contact may give rise to security as well as hygienic concerns among users. Fingerprint or palm-print impressions left on the surface by the user may actually be picked up and used to fabricate fake biometric samples to gain unauthorized access. Zheng et al. [13] have investigated this problem by exploring a non-contact, peg free imaging set up that allows users the freedom of presenting their hands at any orientation, as long as the major part of the hand is captured. They employ a digital color camera to acquire hand images for the authentication. However, the reliability of results in [13] is very low as the experimental results are presented on very small database of 20 subjects. Kumar [24] has also recently investigated the contact-free hand identification and illustrated promising results on the publically available contact-free database from 234 subjects.

1.2. Preprocessing and feature extraction

Prior to feature extraction, acquired hand images are usually processed to obtain a binary image of the hand or sometimes, a hand contour. In most cases, a simple thresholding scheme followed by morphological operations can be used to segment the hand from the background. Figure 1 shows the typical hand geometry features extracted from the silhouette of the hand. Finger length is computed as the distance from the finger tip to its base along the orientation of the finger. Finger width measurements are made at a number of evenly spaced points along the finger length. Finger perimeter refers to the number of pixels on the finger contour. All the measurements shown in figure 1 are usually made in terms of pixels. Please note that measurements from thumb have been found to be unreliable and therefore, in most cases hand geometry features are extracted only from the remaining four fingers. This is especially true in the case of peg free image acquisition systems where the variations in measurements of the thumb are extremely large.

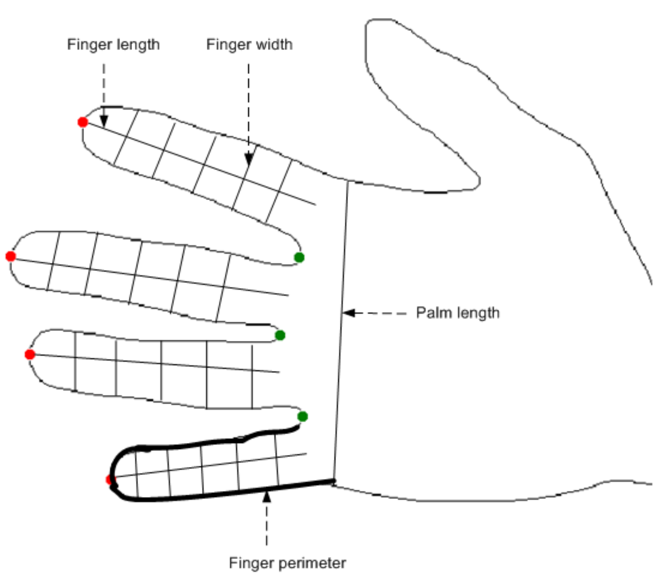

Figure 1. Commonly used 2D hand geometric features marked on a hand silhouette.

Hand geometry system described in [2] measures features such as finger length, finger width and thickness of the hand along 16 different axes. Finger thickness features is computed from the lateral view of the hand. Authors propose to model the gray level profile along the measurement axis for feature extraction. Instead of explicitly measuring geometry features on the hand, authors in [3] and [9] propose to align finger shapes (contours) from a pair of hand images. In order to deal with the deformation of the hand shape (contour) caused by the movement of fingers, authors individually align respective pairs of fingers from the hand images. Sanchez-Reillo et al. [1] extracted an extended set of geometry features from the contour of the hand. In addition to the length and width features from the fingers, various angles and deviations at specific points on the fingers are extracted. A feature selection scheme, based on the discriminatory power of the features, is used to reduce the dimension of the feature vector.

Hand geometry systems that do not employ pegs to register/align hand images usually locate key points (commonly finger tips and valleys) in the hand image (see figure 1). This information can be used to align hand images prior to feature extraction. An alternate approach would be to extract features that are invariant to translation and rotation of the hand in the image plane. Authors in [8] explored one such method by modeling finger contours using implicit polynomials and computing algebraic invariants (features) from polynomial coefficients. The approach proposed in [14] represents hand shapes using Zernike moments that are invariant to transformation and scale. The resulting high dimensional feature vector undergoes a dimensionality reduction technique, PCA. Yörük et al. [11] applied dimensionality reduction techniques on the binary images of the hand that are pre aligned using orientations of the fingers. Zheng et al. [13] proposed hand geometry technique using projective invariant hand features. Feature points detected on the fingers creases are used to compute the projective invariant hand features. Kumar et al. [23] demonstrated that discretization of the hand geometry features leads to significant improvement in performance. Various hand geometry features such as finger lengths/widths, palm length/width, hand length and perimeter are extracted and discretized before matching.

1.3. Feature matching

Feature matching process computes the similarity (or dissimilarity) between the user's feature vector and the one stored during the enrolment. Various matching metrics proposed in the literature include Euclidean distance [1],[2],[13],[14] absolute distance [2], hamming distance [1], normalized correlation [4], cosine similarity [12] and Mahalanobis distance [8]. In addition to these simple matching metrics various trainable classifiers such as radial basis function (RBF)[1], support vector machine (SVM) [23] and Gaussian mixture model (GMM)[1] have also been used to classify the user's feature vector in to genuine or impostor class. Approaches based on alignment of hand contours use metrics such as mean alignment error [3], goodness of alignment [9] (based on finger width measurements) to compare a pair of hand shapes.

Match score generated from feature matching process is used to make a decision as to whether the user is a genuine or an impostor. This decision is usually made based on whether the match score is above or below a given threshold.

2. 3D Hand Geometry

Most of the hand geometry systems/techniques proposed in the literature is based on user's two dimensional hand images. These approaches extract various features from the binarized version of the acquired hand image. Unique information in such binary images is very limited, leading to low discriminatory power for hand geometry biometric systems and thus they are suitable only for small scale applications. With the advances in 3D image acquisition technology, two and three dimensional images of the hand can be acquired simultaneously. Features from these images can be combined to significantly improve the performance. Following sections provide a detailed discussion on different processing modules and approaches for three dimensional hand geometry systems.

2.1. Imaging techniques

Image acquisition module in a 3D hand geometry system captures a range image of the user's hand. Active 3D scanners are usually preferred as they can effectively capture dense and accurate 3D data. Woodard et al [6] are perhaps the first researchers to work on the range images of the hand for biometric recognition/verification. Their approach [6] uses laser based vivid 910 3D scanner [30] to simultaneously acquire color and registered range images of the hand. In order simplify the hand segmentation process, users were requested to place their right hand against a wall covered with black cloth. In another system developed by Malassiotis et al. [5], users were asked to hold their hand in front their face while an in-house developed low cost 3D sensor was used to capture color and range images of the back surface of the hand. 3D sensor employed in their system consisted of a color camera and a standard video projector.

2.2. Preprocessing and feature extraction

Segmentation of the hand in the acquired range images can be made simple by making use of the simultaneously captured (and registered) color or intensity image. Woodard et al [6] worked on a combination of edge and skin detection algorithms to segment hand from the uniform background. Convex hull of the hand contour was used to locate finger valleys and to extract index, middle and ring fingers from the range image of the hand. Malassiotis et al. [5] employed a more complex approach to segment the hand from other parts of the body appearing in the image. Working solely on range images, authors use mixture of Gaussians to model and to subsequently segment hand.

Various features have been proposed for 3D hand/finger geometry biometric. The approach proposed in [11] investigates the pattern distorted by the shape (or curvature) of the hand. The distorted pattern captured by a CCD camera is coded by quad-tree to extract one dimensional binary features. Though this approach does not extract 3D features from the range image of the hand, it essentially utilizes the 3D surface features in an indirect manner. Woodard et al [6] computed shape index, defined in terms of principal curvatures, at every pixel in the range images of fingers and stored as feature templates for matching. The approach in [5] extracts two signature functions, namely, 3D width and mean curvature at a number of cross finger sectional segments. Features computed for four fingers are concatenated to form a feature vector.

2.3. Feature matching

Similar to the 2D hand geometry matchers, simple distance metrics can be used to match hand geometry features extracted from range images. In the literature, normalized correlation [6] and L_1 distance metric [5] are employed for 3D feature matching.

3. Performance

Hand geometry biometry systems based on 2D as well as 3D features have been shown to offer sufficiently high accuracy to reliably authenticate individuals. Researchers have been exploring various approaches to improve the performance of the existing systems. Table 2 provides a comparative summary of various hand geometry approaches discussed in this chapter.

Table 2: Comparative summary of some of the approaches for hand geometry authentication

Reference	**Methodology**	**Imaging**		**Database size (Users)**	**Performance (EER %)**
		Modality	**Pegs**		
[2]	Measurements are made along 16 different axes, and matched using weighted Euclidean distance	2D	YES	50	6[1]
[3]	Individual finger shapes are aligned and a *shape distance* (Mean alignment error) is computed as match score	2D	YES	53	2.5-3[1]
[1]	Feature vector comprises several width, height and angle measurements. GMM is used for matching	2D	YES	20	6[1]
[4]	Feature vectors comprising 16 geometry measurements are matched using normalized correlation	2D	NO	100	8.5
[9]	Fusion of invariants from implicit polynomials and geometric features	2D	NO	28	1
[10]	Individual finger shapes are aligned using a elliptical model and finger tip/valley information	2D	NO	108	2.4
[6]	Shape index image is extracted from range images of fingers and is matched using normalized correlation coefficient	3D	NO	177(probe) 132(gallery)	5.5
[5]	Feature vectors comprising 96 curvature and 3D finger width measurements are matched using L_1 distance	3D	NO[2]	73	3.6
[11]	Independent Component Analysis (ICA) on binary images of the hand. Feature vectors are matched using cosine	2D	NO	458	2

[1] Equal error rate has been approximated from the ROC plot reported in the paper

[2] System acquires hand images in a completely contact free manner

	similarity measure				
[14]	Principal Component analysis (PCA) on extracted higher order Zernike moment features. Reduced feature vectors are matched using Euclidean distance	2D	NO	40	2
[23]	Discretization of hand geometry features to improve the performance	2D	NO	100	1.9
[13]	Feature points on finger creases are detected and used to compute projective invariant features. Feature vectors are matched using normalized Euclidean distance	2D	NO[2]	23	0

4. An Example: Hand geometry system based on 3D features

In this section, we illustrate an authentication system based on 3D hand geometry features. The system utilizes a laser based 3D digitizer [10] to acquire registered color and range images of the presented hands in a completely contact-free manner, without using any hand position restricting mechanism. The block diagram of the system is shown in figure 2. Major processing modules include image normalization (in the pre processing stage), feature extraction and feature matching. Details of these processing steps are provided in the following sections.

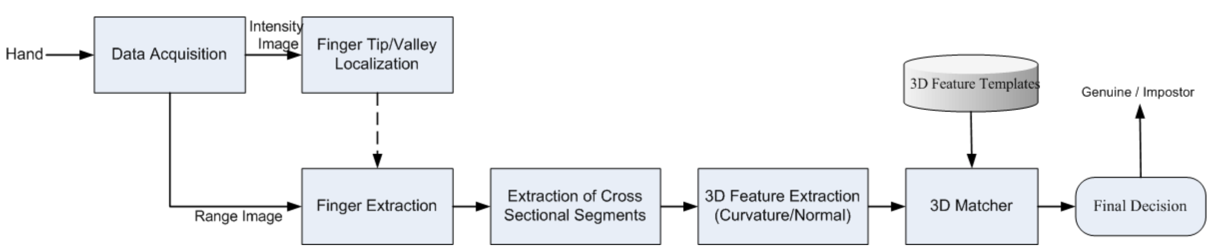

Figure 2. Block diagram of the biometric system utilizing 3D hand geometric features

4.1. Pre processing and finger extraction

The first major step in is to locate finger tips and finger valleys in the acquired image. These reference points are then used to determine the orientation of each finger and to extract them from the input hand image. Since there is a pixel-to-pixel correspondence between the intensity and range image, the acquired color image can be utilized to determine key points and orientation. The steps involved in the process of extracting fingers are illustrated in figure 3 and figure 4. To start with, the two dimensional image is binarized using Otsu's threshold [7]. Resulting binary image is further processed using morphological operators to remove small regions that are not part of the hand. Boundary pixels of the hand in the processed binary image are then identified using the 8-connected contour tracing algorithm. Plotting the distance from the reference point R (in figure 3(b)) to every point on the extracted hand contour, we obtain a curve as shown in figure 4(a). Local minima and local maxima on this plot correspond to finger tips and finger valleys, which can be easily located. In order to estimate the orientation of each finger, four points on the finger contour (two points each on both sides of the fingertip) at fixed distances from the finger tip are identified. Two middle points are computed for corresponding points on both side and are joined to obtain the finger orientation. Having determined the finger orientation and finger tip/valley points, it is straightforward task to extract a rectangular region of interest for fingers.

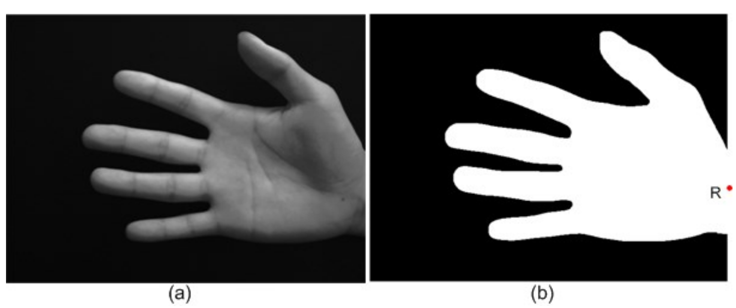

Figure 3. Pre processing stages (a) Acquired intensity image (b) Binary hand image after thresholding and morphological operations

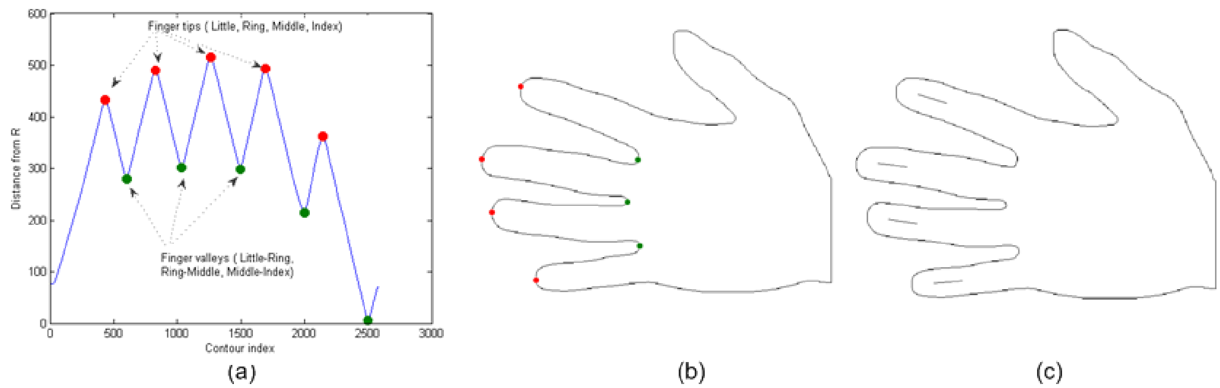

Figure 4. Locating finger tips and valleys (a) Distance from the reference R to points on the contour (b) Finger tips and valleys located (c) Estimated finger orientations

The process of finger extraction discussed above can handle rotation and translation of the hand in the image plane, which are inevitable in a peg free data acquisition set up.

4.2. 3D finger feature extraction

Based on the finger localization algorithm discussed in the previous section, individual fingers can be located and extracted from the acquired range image. Each of the four finger range images is further processed for feature extraction. For each finger, a number of cross sectional segments are extracted at uniformly spaced distances along the finger length. The next step in the feature extraction process is to compute two representations, namely, mean curvature and unit normal vector, for every data point on the extracted segments. Before computing these features, a two dimensional polynomial is used to model the data point and its neighbors. The mean curvature and normal vector features can then be computed for the fitted 2D polynomial by estimating numerical partial derivates of the polynomial at each data point. A 2D polynomial $f(x,y)$ has the following form

$$f(x,y) = c_{00} + c_{10}x + c_{01}y + c_{11}xy + c_{20}x^2 + c_{02}y^2 \tag{1}$$

where x and y are the two dimensional coordinates of a data point. The expression for mean curvature of a 2D polynomial in terms of its coefficients is given by

$$\kappa_{2D} = \frac{(1+c_{10}^2)c_{02} + (1+c_{01}^2)c_{20} - c_{10}c_{01}c_{11}}{(1+c_{10}^2 + c_{01}^2)^{3/2}} \tag{3}$$

Mean curvature in equation 3 is computed for every data point on the cross sectional segments and stored as feature templates in the database. Figure 5(a) shows a cross sectional finger segment extracted from the 3D finger and the corresponding mean curvature plot (in figure 5(b)). In addition to the curvature feature, surface normal vector can be computed at every data point on the segment.

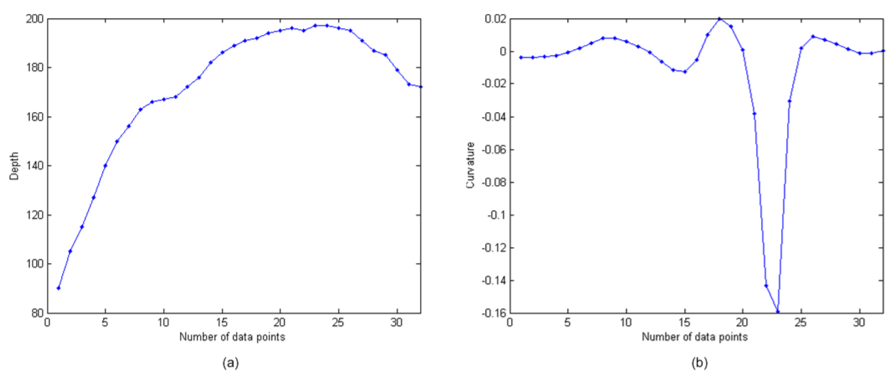

Figure 5. (a) A cross sectional finger segment and (b) its computed curvature features

4.3. 3D feature matching

In the matching stage, features extracted from each of the four fingers are matched individually and then combined to obtain a final matching score. Assume we have extracted features for N_s number of cross sectional segments from template and probe (query) fingers represented by T_i and Q_i respectively, where the subscript i represents the index for fingers and takes values from 1 to 4 for little, ring, middle and index fingers.

Matching of curvature features from a corresponding pair of fingers (denoted as s_i^c) is based on the cosine similarity metric and the match score is computed as

$$s_i^c = \frac{1}{N_s}\sum_{j=1}^{N_s}\phi_i^j \quad \text{where,} \quad \phi_i^j = \begin{cases} \dfrac{T_i^j.Q_i^j(1:l_T^j)}{\left|T_i^j\right|\left|Q_i^j(1:l_T^j)\right|} & \text{if} \quad l_T^j < l_Q^j \\ \dfrac{T_i^j(1:l_Q^j).Q_i^j}{\left|T_i^j(1:l_Q^j)\right|\left|Q_i^j\right|} & \text{otherwise} \end{cases} \tag{7}$$

where l_T^j and l_Q^j are the number of feature points on the j^{th} cross sectional segment of the template (T_i^j) and query (Q_i^j)fingers respectively. $S_{curv}(= \frac{1}{4}\sum_{i=1}^{4} s_i^c)$ is the final score generated from curvature feature matching as illustrated above.

4.4. Performance evaluation

This section provides a discussion on the performance evaluation of the system on a database of 3,540 right hand images. For image acquisition, each user holds his/her right hand in front of the scanner at a distance of about 0.7 m. No constraints were employed to confine the position of the hand nor were the users instructed to remove any jewelry that they were wearing. Users were only asked to hold their hand with their palm approximately parallel to the image plane of the scanner and inside the imaging area. Figure 6 shows a picture of the data acquisition set up as well as sample hand images (range as well as color) acquired using this imaging set up. Figure 7 depicts the overall 3D hand geometry performance resulting from the combination of curvature and normal features. As shown in figure 8, the combination of the 3D hand geometry features achieves an Equal Error Rate (EER) of 3.8%. This result clearly demonstrates that features extracted from 3D hand images carry significant discriminatory information to authenticate individuals.

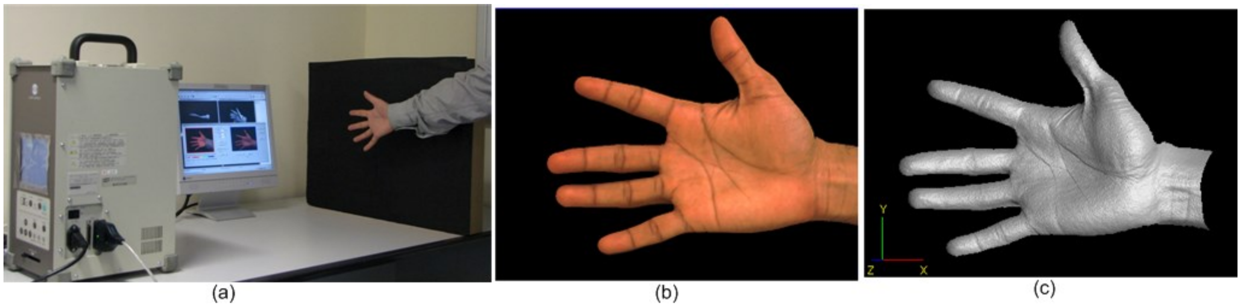

Figure 6. (a) Image acquisition set up and (b) An example of the acquired color and range images

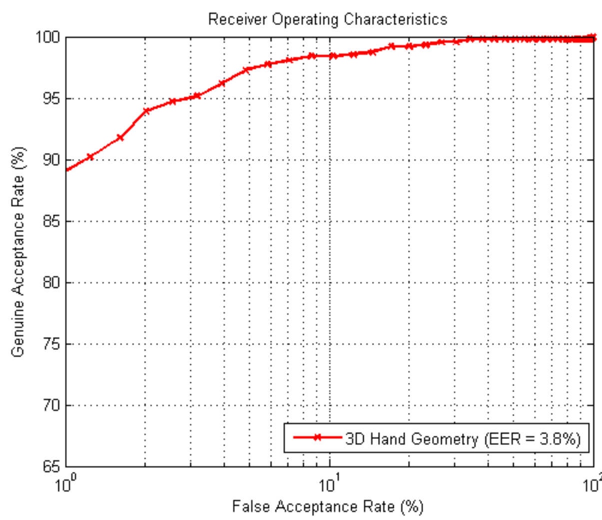

Figure 7. ROC curves showing the performance 3D hand geometric features

5. Summary

This chapter provided a discussion on various methodologies/techniques available for the hand geometry biometrics. A detailed description of the design of a biometric system using 3D hand geometry features is also presented. While the history of commercial hand geometry systems dates back over three decades, academic research addressing critical issues lagged behind and appears to have begun only in late nineties. However, literature currently available in the public domain clearly shows that the research has now caught up with and has in fact transcended the commercially available systems. Majority of the early systems employed pegs to restrict hand placement in order to simplify the subsequent processing steps. This, however, caused inconvenience to the users. Several researchers have addressed this problem by proposing approaches to do away with pegs and thus contributed to the increase in user friendliness of the hand geometry systems. Recently, a few researchers have gone even further and came up with techniques that allow users to simply hold their hand in front of the camera, in a completely unconstrained manner, in order to get authenticated. These promising attempts will certainly help to make the hand geometry as acceptable and popular as face biometrics. However, these systems need to be rigorously evaluated on larger databases before they can be deployed for real world applications. In addition, only a few researchers have explored the use of 3D hand geometric features. Three dimensional hand features can be simultaneously extracted and combined to significantly improve the performance the system. Therefore there is tremendous scope for further research in this direction. Finally, there is a pressing need to develop anti spoofing measures for hand geometry systems, especially in view of the ease with which researchers have been able to circumvent a commercially available hand geometry system [17]. Anti spoofing measures proposed in the literature [25] to detect fake fingerprints based on liveness detection can very well be employed in hand geometry systems. However, further research and development efforts are required to adapt these techniques and design hand geometry systems that can thwart attacks based on fake hands.

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