A New Approach to Hand-Based Authentication

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ABSTRACT

Hand-based authentication is a key biometric technology with a wide range of potential applications both in industry and government. Traditionally, hand-based authentication is performed by extracting information from the whole hand. To account for hand and finger motion, guidance pegs are employed to fix the position and orientation of the hand. In this paper, we consider a component-based approach to hand-based verification. Our objective is to investigate the discrimination power of different parts of the hand in order to develop a simpler, faster, and possibly more accurate and robust verification system. Specifically, we propose a new approach which decomposes the hand in different regions, corresponding to the fingers and the back of the palm, and performs verification using information from certain parts of the hand only. Our approach operates on 2D images acquired by placing the hand on a flat lighting table. Using a part-based representation of the hand allows the system to compensate for hand and finger motion without using any guidance pegs. To decompose the hand in different regions, we use a robust methodology based on morphological operators which does not require detecting any landmark points on the hand. To capture the geometry of the back of the palm and the fingers in sufficient detail, we employ high-order Zernike moments which are computed using an efficient methodology. The proposed approach has been evaluated on a database of 100 subjects with 10 images per subject, illustrating promising performance. Comparisons with related approaches using the whole hand for verification illustrate the superiority of the proposed approach. Moreover, qualitative comparisons with state-of-the-art approaches indicate that the proposed approach has comparable or better performance.

Keywords: Biometrics, Hand-based authentication, Zernike moments

1. INTRODUCTION

Hand-based authentication is among the oldest live biometrics-based authentication modalities. The existence of several hand-based authentication commercial systems and patents indicate the effectiveness of this type of biometric. Hand-based verification systems are usually employed in small-scale person authentication applications due to the fact that geometric features of the hand (e.g., finger length/width, area/size of the palm) are not as distinctive as fingerprint or iris features. There are several reasons for developing hand-based authentication systems. First, hand shape can be easily captured in a relatively user friendly manner by using conventional CCD cameras. Second, this technology is more acceptable by the public in daily life mainly because it lacks a close connection to forensic applications. Finally, there has been some interest lately in fusing different biometrics to increase system performance.[1,2] The ease of use and acceptability of hand-based biometrics make hand shape a good candidate in these heterogeneous systems.

The geometry of the hand contains relatively invariant features of an individual. Therefore, most hand-based verification systems rely on explicit geometric measurements. First, the user is asked to place his/her hand on a flat surface and align it, with the help of some guidance pegs. Then, several hand-crafted geometric features (e.g. length, width and height of the fingers, thickness of the hand, aspect ratio of fingers and palm, etc.) are extracted. The alignment operation simplifies the feature extraction process and allows high processing speeds. However, several studies have reported that, peg-based alignment is not very satisfactory and represents, in some cases, a considerable source of failure.[3,4] Removal of pegs, to improve convenience and robustness, and use of more sophisticated feature extraction techniques to capture the shape of the hand in more detail represent promising research directions in this area.

In peg-free systems, fingers are not guaranteed to be at the same position and orientation at different acquisition times. Therefore, they need to be segmented and identified in the input images. Analysis of the silhouette

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contour to locate fingertips and palm-finger intersections, which basically corresponds to curvature local maxima, provides an effective solution to the segmentation problem.[5,6] Once the fingers have been segmented, geometric features such as finger length and width can be measured at predefined points along the finger axes[2,6–8] to build peg-free extensions of conventional systems.

In this paper, we consider a component-based approach to hand-based verification. Our objective is investigating the discrimination power of different parts of the hand in order to develop a simpler, faster, and possibly more accurate and robust verification system. In this context, we propose a new approach that decomposes the hand in different regions, corresponding to the fingers and the back of the palm, and performs verification using information from certain parts of the hand only. This in in contract to traditional approaches that extract information from the whole hand and employ guidance pegs to fix the position and orientation of the hand. Our hand decomposition methodology employs morphological operators and does not require extracting any landmark points on the hand. To represent the geometry of the fingers and the back of the palm in sufficient detail, we employ high-order Zernike moments which are computed using an efficient methodology.[9] This is also in contract to traditional approaches that extract hand-crafted measurements and rely on accurate detection of landmark points on the hand. Our approach operates on 2D images acquired by placing the hand on a flat lighting table. To simplify segmentation, we require that subjects stretch their hand prior to placing it on the lighting table to avoid touching fingers. However, no other restrictions were imposed on the subjects. An earlier version of this work, involving the use of the whole hand for verification, has been proposed by Amayeh et al.[10]

The rest of the paper is organized as follows: in Section 2, we provide an overview of the proposed system. Section 3 provides the details of segmenting the hand in parts. The feature extraction process, which mainly involves the computation of high-order Zernike moments of the fingers and the back of the palm, is discussed in Section 4. Experimental results and comparisons are reported in Section 5. Finally, Section 6 provides our conclusions and plans for future work.

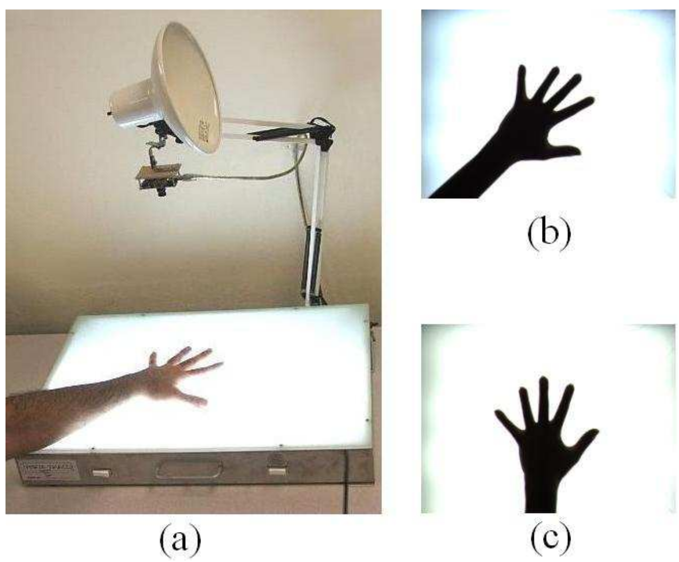


Figure 1. (a) Image acquisition system, (b, c) Images of the the same hand acquired by the system.

2. SYSTEM OVERVIEW

Our image acquisition system consists of a VGA resolution CCD camera and a flat lighting table, which forms the surface for placing the hand. The direction of the camera is perpendicular to the lighting table as shown in Fig. 1(a). The camera has been calibrated to remove lens distortion. In practical settings, both the camera and the lighting table can be placed inside a box to completely eliminate light interferences from the surrounding environment. The current setting in our laboratory provides fairly high quality images without much effort on our side to control the environment.

When users place their hand on the surface of the lighting table, an almost binary, shadow and noise free, silhouette of the hand is obtained as shown in Figs. 1(b) and (c). During acquisition, subjects are required to stretch their hand and place it inside a rectangular region marked on the surface of the table. This is to ensure the visibility of the whole hand and to avoid perspective distortions. No restrictions were imposed on the orientation of the hand. The image acquired is then binarized and goes through the segmentation module.

During segmentation, the arm is separated from the hand and discarded from further processing. Then, the hand is further processed to segment the palm and the fingers. Feature extraction is performed by representing the geometry of each part of the hand in terms of high-order Zernike moments. The resulting representation is invariant to translation, rotation and scaling transformations. Verification is performed by using information from different parts of the hand. We employ multiple enrollment templates per subject and compute similarity scores using the minimum distance between a query image and the templates of the subject.

3. HAND SEGMENTATION IN PARTS

This stage includes the binarization of the acquired image and its segmentation into different regions corresponding to the arm, hand, back of the palm, and fingers. Our current setting yields very high quality images, which are almost free of shadows and noise. As a result, binarization can be performed using a fixed threshold. To separate the forearm from the hand, first we detect the palm by finding the largest circle that can be prescribed inside the hand-arm silhouette. To segment the hand, we take the intersection of the forearm with the circle's boundary. To separate the fingers from the palm, we filter out the fingers first using morphological closing[11]; then, the palm is subtracted from the hand silhouette to segment the fingers. Specific details are provided below.

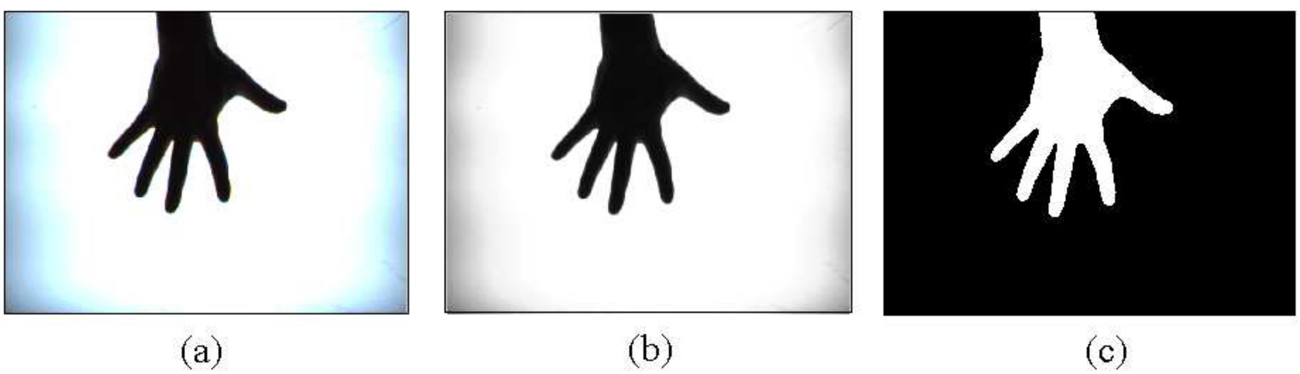
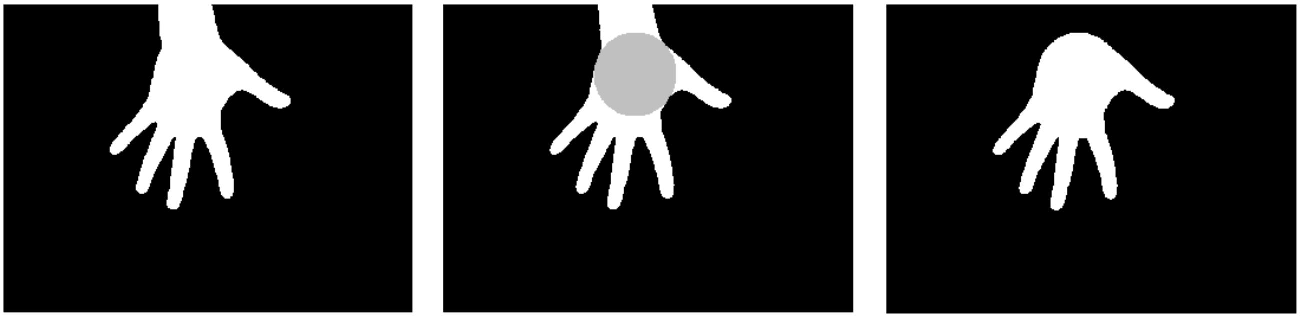


Figure 2. (a) Color image, (b) Gray-scaled image and (c) Binarized image.

3.1. Binarization

The hand images can be captured using a gray scale camera; however, we used a color CCD camera as it was already available in our laboratory. The luminance value of each pixel was used to obtain a grayscale image. Figures 2(a) and (b) show the original color image and gray scale image respectively. The binary value of each pixel was calculated using thresholding. In all the experiments reported here, we used the same threshold value. Figure 2(c) shows the output of the binarization process. The resulting silhouettes are very accurate and consistent due to the design of our image acquisition system. This is critical in our system since high-order Zernike moments are quite sensitive to small changes in silhouette shape.

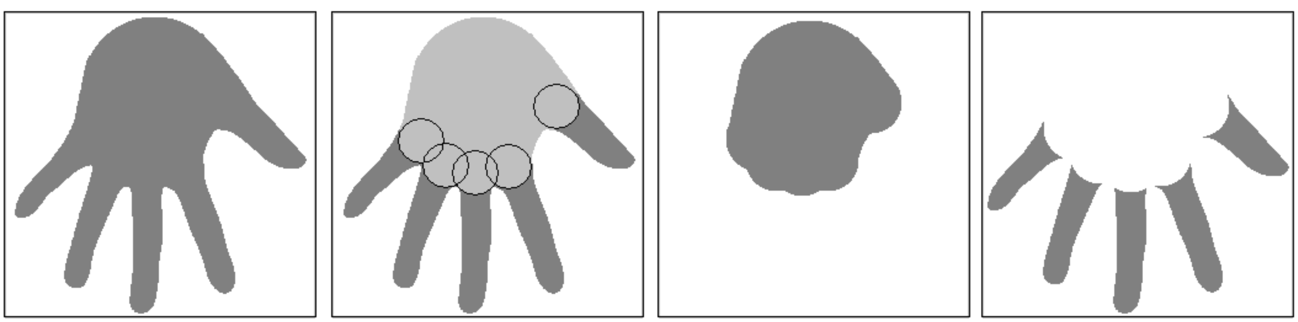


(a) (b) (c)

Figure 3. (a) Binarized image, (b) Largest circle inside of hand-arm silhouette (c) Segmented hand silhouette.

3.2. Hand-Arm Segmentation

The binary silhouette obtained during image acquisition is the union of the hand with the forearm. The forearm does not have many distinctive features while its silhouette, at different acquisition sessions, is not expected to be the same due to clothing and freedom in hand placement (see Figures 1(b),(c)). To segment the forearm, we assume that the user is not wearing very loose clothing on the arm. Under this assumption, the palm becomes the thicker region of the silhouette, which enables us to detect it by finding the largest circle inside the silhouette. We use an iterative scheme based on morphological closing and a circular structuring element[11] to find the largest circle. Figure 3(b) shows the output of the algorithm above on a sample image. Once the largest circle is found, the forearm is segmented by detecting its intersection with the circle and the boundary of the image. Figure 3(c) shows the resulting silhouette after discarding the forearm region.



(a) (b) (c) (d)

Figure 4. (a) Hand silhouette, (b) morphological closing, (c) the result of closing and (d) the result of subtracting the palm from the hand silhouette.

3.3. Palm-Finger Segmentation

During image acquisition, subjects were asked to stretch their hand in order to avoid touching fingers, however, finger motion is unavoidable. The processing steps of the finger segmentation module are shown in Figure 4. First, a morphological closing operator based on a circular disk is applied on the hand image as shown in Figure 4(a). The radius of the structuring element was experimentally set to 25 pixels (i.e., making it thicker than the widest finger in our database). The closing operation filters out the fingers from the silhouette as shown in Figure 4(b) and (c). The remaining part of the silhouette corresponds to the palm, which is subtracted from the hand image to obtain the finger segments shown in Figure 4(d). To extract each finger region and the palm, we use connected components.[12]

3.4. Post-processing of finger regions

A closer examination of the segmentation results shown in Figure 4(d) reveal that the segmented fingers have sharp tails at the locations of separation from the palm. To keep these errors as low as possible, we apply an additional morphological closing on each finger as shown in Figure 5. The structuring element in this case is a simple 4 by 4 square whose elements are equal to one. In the case of the two little fingers shown in Fig. 5, coming from the same hand, eliminating the tails decreases the distance between them from 0.5904 to 0.0901.

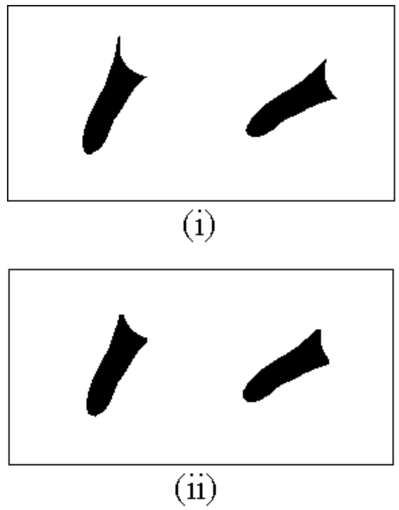


Figure 5. (*i*) Two little finger samples belonging to the same subject, (*ii*) eliminating finger tails using morphological filtering.

4. FEATURE EXTRACTION

The majority of peg-free systems extract various landmark points on the hand (e.g., finger joints) and represent hand shape by explicitly measuring certain geometric features. Alternatively, one can imagine utilizing various shape descriptors to provide a more powerful representation of hand shape, replacing the conventional hand-crafted geometric features. In this study, we represent the geometry of the hand implicitly using region descriptors based on Zernike moments. Using Zernike moments has the potential to provide a richer representation of the shape of the hand. Besides, no landmark points need to be detected in our case.

Zernike moments have been employed in a wide range of applications in image analysis, and object recognition.[13] In the context of our application, they are quite attractive for representing hand shape information due to having minimal redundancy (i.e., orthogonal basis functions[14]), being invariant to translation, rotation, and scale, and being robust to noise.[13] In most applications, the use of Zernike moments has been limited to low-orders only or small low-resolution images due to high computational requirements and lack of accuracy due to numerical errors. Using Zernike moments to represent the geometry of the fingers and the back of the palm has the potential to provide a richer shape representation; however, capturing sufficient details of the shape of the hand would require computing high-order moments.

Although there exist some fast algorithms that rely on approximate polar coordinate transformations,[15–17] they do not yield satisfactory results for our application due to lack of accuracy. To deal with the issues of speed and accuracy, we use an efficient algorithm, proposed by Amayeh et. al,[9] which reduces computational cost without sacrificing accuracy. To preserve accuracy, the algorithm avoids any form of coordinate transformation using arbitrary precision arithmetic. To reduce computational complexity, it avoids recomputing the same terms repeatedly and uses look-up tables.

Each part of the hand is processed independently to compute the Zernike descriptors. We used the average reconstruction error on a large number of images to decide the maximum order that would be useful in the context of our application. Based on the analysis of reconstruction error, the maximum order was set to be 20 for the fingers and to 30 for the back of the palm. Applying the same analysis on the whole hand yielded a maximum order of 70.[10] It should also be noted that, none of the samples in our test database were used to determine these parameters.

5. EXPERIMENTAL RESULTS

In order to evaluate the proposed system, we have collected hand images from 100 people of different age, sex and ethnicity. For each subject, we collected 10 images of his/her right hand during the same session. In each session, subjects were asked to stretch their hand and place it inside a square area drawn on the surface of the lighting table; no other restrictions were imposed on the subjects. To capture different samples within each session, subjects were asked to remove their hand from the lighting table, relax it for a few seconds, and then place it back again. To calculate the distance between a query hand Q and each of the template hands T_i for a given individual in the database, we compute all Euclidean distances between the query and the templates and take the minimum distance:

$$D = arg_i min\{||Q - T_i||\}, i = 1, .., k \tag{1}$$

where k corresponds to the number of templates. If the minimum distance is below a threshold, then verification is considered successful; otherwise the subject is rejected.

In the following subsections, we present experimental results and comparisons to demonstrate the proposed approach. For comparison purposes, first we investigate a baseline system which uses the whole hand for verification.[10] Then, we investigate the discriminatory power of different parts of the hand by implementing a system that performs verification using each part of the hand separately. Finally we provide a qualitative comparison of our system and the state of the art.

5.1. Verification using whole hand

In this case, the arm is segmented from the rest of the hand using the methodology presented in Section 3. Then, the geometry of the whole hand is represented in terms of Zernike moments. As mentioned earlier, representing the whole hand requires using Zernike moments up to order 70 which yields a feature vector containing 1296 components.

To test this approach, we used 5 of samples for each subject as enrollment templates. To capture the effect of template selection, we repeated each experiment 30 times, each time choosing the enrollment templates randomly. The remaining samples were used to construct matching and non-matching sets to estimate the False Acceptance Rate (FAR) and False Reject Rate (FRR) of each system. Figure 6 shows the average ROC curves obtained in this case.

Since the size of the feature vectors was very high, we have also performed experiments using Principal Components Analysis (PCA)[18] to reduce their dimensionality. In each experiment, the eigenvectors were computed from the covariance matrix of the enrolled templates for each subset. In all the cases, we preserved 99.9% of the information in the data, yielding between 252 and 274 features. Fig. 6, shows the average ROC curves using PCA. As it can be observed, PCA improves verification performance slightly.

5.2. Verification using different parts of the hand

To investigate the discriminatory power of each part of the hand, we have built several systems which perform verification using each part of the hand separately. Each system was tested using 5 samples for each subject as enrollment templates. Each experiment was repeated thirty times, reporting average performance for each experiment. To ensure a fair comparison, we used the same training and test data as in the case of the whole hand. To calculate the distance between a given part of the query hand and the corresponding part of a hand template, we used Eq. 1 as before.

Figure 7 shows the average ROC curves for each part of the hand. Quite interestingly, using information from certain parts of the hand yields higher verification accuracy than using information from the whole hand. This is

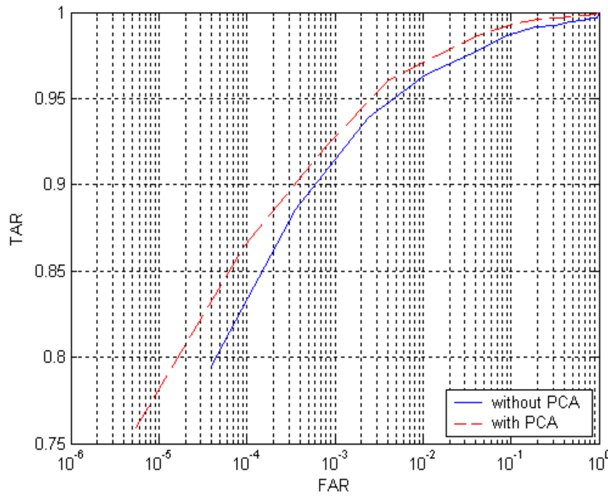


Figure 6. Verification accuracy using the whole hand. The blue curve corresponds to using raw features while the red curve corresponds to using PCA features.

because much lower orders are needed to represent the fingers and the back of the palm. Therefore, the resulting representation is more robust to noise and distortions. Overall, our results indicate that the index, middle, and ring fingers offer the best verification performance. On the other hand, the thumb has the lowest performance among all other parts. This is because it is harder to fix its position due to greater motion flexibility.

For comparison purposes, we have also performed experiments using PCA to reduce the dimensionality of the feature vectors. In all the cases, we preserved 99.9% of information. Table 1 provides the details of our experiments. In this case, PCA does not offer any major improvements.

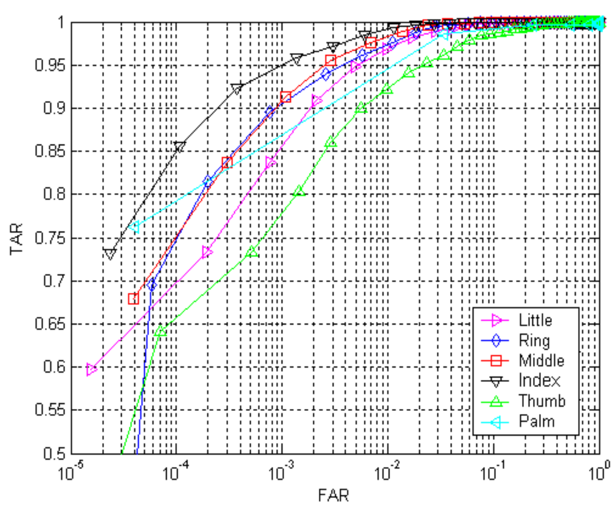


Figure 7. Verification accuracy using different parts of the hand.

Table 1. Comparison of verification accuracy for each part of the hand using raw versus PCA features.

	Hand		Little		Ring		Middle		Index		Thumb		Palm	
Features	Raw	PCA	Raw	PCA	Raw	PCA	Raw	PCA	Raw	PCA	Raw	PCA	Raw	PCA
no. of features	1296	252-274	121	23-24	121	18	121	16	121	16	121	43-45	256	87-96
TAR	97.2	97.8	98.2	98.2	98.4	98.3	98.7	98.6	99.1	99.0	96.4	96.5	98.0	98.1

5.3. Comparative Evaluation

To further investigate the performance of our system, we present a qualitative comparison of the error rates of our system and those reported in the literature shown in Table 2. Since there is no standard acquisition method and, as a result, no benchmark databases, quantitative comparison of different systems are only indicative and not conclusive. To make our comparison fair, for each study considered, we report several other factors such as number of subjects, number of images per person, number of templates, use/no-use of pegs, type of features, and distance measures. The results reported for our system in Table 2, were obtained using 5 enrollment templates. Our database size is comparable to most of the systems reported in the table and our error rates are better than or equal to even the ones reported on much smaller databases.

Table 2. Comparisons with other methods.

Method	Jain[4]	Reillo[19]	Bulatove[8]	Kumar[2]	Yoruk[20]	Our method (Index finger)
Database Size	50×7.2	20×10	70×10	100×10	100×3	100×10
Enrollment	50×2	20×5	70×5	100×5	100×2	100×5
TAR	97.5	94.5	98.5	99.1	98.85	99.1

6. CONCLUSIONS AND FUTURE WORK

We have presented a new hand-based verification approach which decomposes the hand in different parts, corresponding to the back of the palm and the fingers, and performs verification using information certain parts of the hand only. To represent the shape of the fingers and the back of the palm, we use high-order Zernike moments which are computed using an efficient methodology. The proposed approach has certain advantages including that it is peg-free, it does require the extraction of any landmark points, and it is not affected by the orientation and position of the hand or finger movement. The only restriction imposed by our system is that the used must present his hand in a stretched configuration to avoid touching figures. Using information from certain parts of the hand has shown better performance than using information from the whole hand. Using a database of 1000 images from 100 subjects, the best average performance of our system using 5 index finger templates per user was as follows: TAR=99.23% when FAR=1% and EER=0.9%. Qualitative comparisons between our system and other systems reported in the literature indicate that our system performs comparable or better.

For future work, first we plan to investigate the idea of fusing information from different parts of the hand in order to further improve verification accuracy and robustness. Second, we plan to consider approaches for combining multiple templates into a single, "super-template", to reduce memory requirements but also to build more accurate models for each individual. Third, we plan to increase the size of the database in order to perform larger scale experiments and obtain more accurate error estimates. Also, we plan to test the robustness of the method when there is substantial passage time between the template and test images. Finally, we plan to compare our technique with other techniques using the same database to reach more useful conclusions.

ACKNOWLEDGMENTS

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