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SURVEY ON GENDER CLASSIFICATION USING HAND SHAPE

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ABSTRACT

This paper proposes a method of recognizing a handshape using various method. First method is Hand Shape and Texture, This proposes a new bimodal biometric systemusing feature-level fusion of hand shape and palm texture. The proposed combination is of significance since both the palmprint and hand-shape images are proposed to be extracted from the single hand image acquired from a digital camera.second.Second method for gender classification is Kernel Orthogonal Mutual Subspace Method. In this method of recognizing a hand shape using multiple view images. The recognition of a hand is a difficult problem, as its appearance changes largely depending on view point, illumination condition and individual characteristics. To overcome this problem, we apply the Kernel Orthogonal Mutual Subspace Method to shift invariant features, HLAC (Higherorder Local Auto-Correlation), from the multiple view images of a hand. The validity of the proposed method is demonstrated through the evaluation experiments using the multiple view images of ten kinds of hands. Third method is Fingerprint-Based Gender Classification, Gender classification from fingerprints is an important step in forensic anthropology in order to identify the gender of a criminal and minimize the list of suspects search. Fourth method is quadtree techniques. This method by using quadtree techniques, which are able to recognize the hand shape image within an extremely short time. The geometrical shape of a hand is a biometric characteristic of human beings, although it is di€erent even for a twin sibling. This study uses a parallel grating to project onto the backside of a hand. The parallel grating will be distorted by the curvature shape of the hand and processed by image processing techniques for recognition. Fifth method for identification is based on Kernel Orthogonal. sisth method for identification is Zernike moments and Fourier descriptors, To represent the geometry of each part, we use region and boundary features based on Zernike moments and Fourier descriptors. For classification, we compute the distance of a given part from two different eigenspaces, one corresponding to the male class and the other corresponding to female class.

Keywords: *Gender, hand shape and classification.*

INTRODUCTION

Many social interactions and services today depend on gender. In this paper, we investigate the problem of gender classification from hand shape. Our work has been motivated by studies in anthropometry and psychology suggesting that it is possible to distinguish between male and female hands by considering certain geometric features. Our system segments the hand silhouette into six different parts corresponding to the palm and fingers. To represent the geometry of each part, we use region and boundary features based on Zernike moments and Fourier descriptors. For classification, we compute the distance of a given part from two different eigenspaces, one corresponding to the male class and the other corresponding to female class. We have experimented using each part of the hand separately as well as fusing information from different parts of the hand. Using a small database containing 20 males and 20 females, we report classification results close to 98% using score level fusion and LDA (Amayeh *et al.,* 2007).

METHODS

Image Acquisition & Preprocessing: For image acquisition, we have used the system reported in for hand-based authentication. This system consists of a 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. The camera has been calibrated to remove lens distortion. The size of the captured images is 480×640 pixels. Figures 1(a) and (b) show two sample images acquired by this system. Each image goes through a preprocessing stage. First, the image is binarized using thresholding. Since image quality is very high due to our set-up (i.e., almost free of shadows and noise), a fixed threshold works well. After binarization, we segment the hand silhouette into six different regions corresponding to the palm and the fingers. Segmentation is performed using an iterative process based on morphological filters. Figure 1(c) shows the segmentation results on the image of Figure 1(a).

Feature Extraction: Once the hand silhouette has been segmented into different regions, each region is represented by a set of features. We have experimented with two different MPG-7 shape descriptors (Amayeh *et al.,* 2007) to represent the geometry of the fingers and the palm. In particular, MPG-7 divides shape descriptors in two categories: contour-based and region-based. Contourbased shape descriptors use the shape's boundary to extract shape information, while region-based shape descriptors exploit the shape's region to represent shape information. In this work, we experimented with ZMs and FDs, both of which are listed in the MPEG-7 standard.

Using Zernike Moments for Hand Shape Verification: One can imagine utilizing various shape descriptors to provide a more powerful representation of the shape of the hand, replacing the conventional geometric features. In this project, we will use high-order Zernike moments for representing hand shape geometry. The method requires 2D hand silhouette images which can be acquired by placing the hand on a lighting table (or a scanner) without any guidance pegs. Moreover, it does not require extracting any landmarks on the hand (e.g., finding finger joints), a process which could be prone to errors. Using Zernike moments for hand-based authentication requires fast computation of high-order moments as accurately as possible, in order to capture the details of the hand shape. To deal with these requirements, we are using the algorithm described in Section 3. To determine the maximum order of Zernike moments needed for capturing the shape of the hand satisfactorily, we can use the average reconstruction error (i.e., Eq. 5) on a large number of hand images. Fig. 3 shows the reconstruction error for different orders. As it can be observed, the error almost saturates for orders higher than 70. Fig. 3(a), shows the reconstructions for different orders. The saturation observed in Fig. 3(b) is also visually evident in Fig. 3. Based on these experiments, the the maximum order chosen in our system was 70 Original and (b) reconstructed images (left to right, top to bottom) up to order 10, 20, 30, 40, 50, 60, 70, 80, and 90; (c) reconstruction error. Zernike moments up to order 70 yield a feature vector of 1296 components. To reduce template size, Principal Component Analysis (PCA) can be used to reduce the dimensionality of the Zernike feature vectors. Using only 30 components, we were able to capture 99% of the information. For matching, the Euclidean distance can be used. Since we use multiple templates for each subject, our similarity criterion is based on the minimum distance between the query and the templates.

Experimental Results: In order to evaluate the approach, we used data from 40 people of different age and sex. For each subject, we collected 10 images of their right hand during the same session. Besides asking the subjects to stretch their hand and place it inside a square area drawn on the surface of the lighting table, no other restrictions were imposed (Fig. 4). To capture different samples, subjects were asked to remove their hand from the lighting table, relax for a few seconds, and then place it back again. As a result, finger movements were unavoidable. For example, the middle and ring fingers are more apart from each other in Fig. 4(d) than in Fig. 4(c).

Our experimental results show that Zernike moments can tolerate certain finger movement (e.g., 6 degrees rotation about the axis perpendicular to the joint of the finger with the palm), however, they are more sensitive when fingers move close to each other. Interestingly enough, finger motion does not affect high-order moments significantly more than low-order moments. Also, Zernike moments cannot tolerate very well situations where the hand is bent at the wrist. In our database, the maximum distance between samples was 0.6556. The mean distance between samples of the same subject (i.e., 1800 pairs of hands) was 0.2063, while the mean distance between samples of different subjects (i.e., 76,200 pairs of hands) was 0.4507. We used different number of samples (e.g., 3, 4, and 5) for each subject as enrollment templates. To capture the effect of template selection on overall system performance, we repeated each experiment ten times, each time choosing the enrollment templates randomly. The remaining samples were used to construct matching and non-matching sets to estimate False Acceptance Rate (FAR) and False Reject Rate (FRR). Figs. 5(a), (b), and (c) show the average ROC curves using 3, 4 and 5 templates per subject respectively. For comparison purposes, our tests were performed using both Zernike moments and PCA features. In all cases, performance was better using PCA was rather than using raw Zernike moments except for very low FAR values. Moreover, we observed that the error rates decrease to a great extent with an increase in the number of templates, which also enforces the use of PCA. Fig. 2. Average ROC curves using (a) 3, (b) 4, and (c) 5 templates for each subject; the solid and dashed curves correspond to the raw Zernike moments and PCA features respectively. It should be mentioned that using the whole hand for authentication suffers from finger motion. To deal with this issue, the method has been extended by decomposing the silhouette of the hand in different regions, corresponding to the palm and fingers, and fusing information from different parts of the hand. To capture the geometry of the palm and the fingers, high-order Zernike moments are used again.

GENDER CLASSIFICATION USING HAND DIMENSION

Introduction: Sex determination is the vital part of identification, which is often required in medico-legal practice. The problem of identification mainly arises when the body is recovered in advanced stage of decomposition, mutilated state, fragmented remains and skeletanized form. There are lots of researches going on for assessing stature, sex, race, etc from anthropometric measurements of different parts of body for identification purpose (George, 1930). Many physical anthropometric studies show the gender difference. The present study has been conducted to find out co-relation of hand dimensions with sex (male/female).

Methodology: The study was conducted in the Department of Forensic Medicine & Toxicology, SSR Medical College, Mauritius in the year 2005. The material consisted of 250 young and healthy students (125 males and 125 females) in the age group of 18-30 years. The hand length was measured as straight distance between distal crease of wrist joint and the most anterior projecting point i.e. tip of middle finger. The breadth of hand was measured as straight distance from the most laterally placed point on the hand of 2nd metacarpal to the most medially placed point located on the head of 5th metacarpal. The measurements were taken by using anthropometric sliding and spreading calipers, and measuring tape. Similar to foot index 4, the hand index was calculated by dividing the hand breadth by hand length and multiplied by 100. The data were statistically analyzed to determine sex by measurements of hand.

Results- Hand lengthIn males, the right hand length varied from 15.30cm to 21.00cm (mean 18.89cm & SD 0.88) and left hand length varied from 15.40cm to 20.08cm (mean 18.90cm & SD 0.87). In females, the right hand length varied from 14.80cm to 20.40cm (mean 17.22cm & SD 0.92) and left hand length varied from 14.80cm to 20.40cm (mean 17.22cm & SD 0.93).(Table1).

Hand breadth: In males, the right hand breadth varied from 7.30cm to 9.40cm (mean 8.45cm & SD 0.40) and left hand breadth varied from 7.20cm to 9.40cm (mean 8.42cm & SD 0.40). In females, the right hand breadth varied from 6.70cm to 8.80cm (mean 7.48cm & SD 0.38) and left hand breadth varied from 6.60cm to 8.70cm (mean 7.42cm & SD 0.37)(Table 2). In males, the hand index ranged from 44.02 (18-19 yrs) to 45.05 (19-20 yrs). In females, it ranged from 42.65 (more than 22 yrs) to 43.79 (18-19 yrs) (Table 3 & 4). Sometimes, fragments of soft tissues are found disposed off in the open, in ditches, or rubbish dumps, etc. and this material is brought to forensic pathologist for examination. One of the important objectives of examination is identification. In our study, we tried to establish the co-relation between hand index and sex. Males had an average hand length and breadth about 1cm greater than the females' hand length and breadth. These findings were consistent with the study conducted by Kodak. In all age groups, the hand index in males was found to be more than 44, and in females, it was less than 44. Therefore, this value i.e. 44 can be used as deviation point for the determination of sex. Thus the present study indicates a positive correlation between an individual's hand dimensions and gender. Thus sex can be determined by hand index with fair accuracy. Further researches are needed in this field.

FINGERPRINT-BASED GENDER CLASSIFICATION

Introduction: Gender classification from fingerprints is an important step in forensic anthropology in order to identify the gender of a criminal and minimize the list of suspects search. A dataset of 10-fingerprint images for 2200 persons of different ages and gender (1100 males and 1100 females) was analyzed. Features extracted were; ridge count, ridge thickness to valley thickness ratio (RTVTR), white lines count, ridge count asymmetry, and pattern type concordance. Fuzzy CMeans (FCM), Linear Discriminant Analysis (LDA), and Neural Network (NN) were used for the classification using the most dominant features. We obtained results of 80.39%, 86.5%, and 88.5% using FCM, LDA, and NN, respectively. Results of this analysis make this method a prime candidate to utilize in forensic anthropology for gender classification in order to minimize the suspects search list by getting a likelihood value for the criminal gender. Fingerprint identification and classification has been extensively researched in the literature, however very few researchers have studied the fingerprint gender classification problem (Amayeh *et al.,* 2006).

Materials and Methods: In our gender classification analysis from fingerprints, we acquired the data first then we extracted the whole features for every finger, averaged the features for the person's 10 fingers, and classified the gender of each person based on different combinations of these features. The overall features include ridge count, RTVTR, fingerprint pattern type, white lines count, pattern type concordance between the corresponding left-right fingerprints, and ridge count asymmetry between the left-right corresponding fingerprints. Statistical analysis was performed for pattern types, ridge count, and ridge counts along pattern types.

Dataset: A dataset of 10-fingerprints for 2200 persons of different ages and gender (1100 males, and 1100 females) were scanned from their ink prints as shown in figures 1 and 2, and were analyzed for the ridge count, and pattern type features. The RTVTR, and white lines count features were analyzed for 255 persons (150 males, and 105 females).

Features Extraction

Ridge and Valley Thicknesses: The average ratio between the ridge thickness and the valley thickness for each of the subject's fingerprints was calculated automatically, and an average ratio was calculated for every subject. The fingerprint image was divided into 30x30 non overlapping blocks. The local ridge orientation within each block was calculated as shown in Figure 5. The projection profile of the valleys and ridges along a line perpendicular to the local ridge orientation in each block was calculated, and the projection profile was binarized using 1D optimal thresholding. The resultant binary profile represents the ridges and valleys in this block, the high binary value represents the valleys and the low binary value represents the ridges. Figure5 shows two blocks of female and male fingerprints, and their projection and binary profiles. The average RTVTR was calculated for each block. The uniformity of ridges and valleys within the blocks varies, for blocks having non uniform ridges and valleys due to the low quality of the fingerprint image in this region, the ridge orientation estimation is usually incorrectly estimated, and thus the RTVTR calculated for this block is incorrect, so only the blocks having the best quality should contribute to the average RTVTR calculated for this fingerprint. For each block, a quality index was calculated as the average difference between the values of successive singular points (Minimas and Maximas) of the projection profile, blocks of good quality have higher quality index than those of bad quality. Figure 5 shows a good quality block, having quality index of 0.244, and correctly estimated RTVTR of 1.67, and a bad quality block, having quality index of 0.061, and incorrectly estimated RTVTR of 1.06. The blocks were arranged in a descending order based on their quality index, and the RTVTR of the best 15 were averaged and taken as the average RTVTR for this fingerprint.

White Lines Count, Ridge Count, Pattern Type, Pattern Type Concordance, and Ridge Count Asymmetry: The white lines count and ridge count were extracted manually for each fingerprint, an average white lines count as well as the ridge count was calculated for each subject (Fig 6-9). Pattern type was extracted manually for each fingerprint, and the pattern type concordance was calculated for the fingerprints of each right-left corresponding fingerprint pair for the subject, such that the concordance value is 1 if the corresponding fingerprints have the same pattern type, and is 0 otherwise, then the sum of the 5 fingerprint pair's concordance values was calculated. The ridge count asymmetry between the right-left corresponding fingerprints for a subject was calculated, the asymmetry is 1 for a left-right corresponding fingerprint pair if the ridge count of the left fingerprint is greater than the right one, is –1 if it is smaller, and is 0 if both ridge counts are equal. The sum of the asymmetry values of the 5 fingerprint pairs of the subject was calculated

RESULTS

White Lines Count and RTVTR Statistics: The female's fingerprint is characterized by a high RTVTR, while the male's fingerprint is characterized by low RTVTR, with the exception of small percentage of male's fingerprints having high RTVTR, and female's fingerprints having low RTVTR. Figure 6 shows histograms of the RTVTR of the females, with $\mu=1.05473$, $\sigma=0.1245$, and the males, with $\mu=0.9494$, $\sigma=0.1045$, with t-value=6.866, and ρ-value=5.158e-11.

Classification: First we applied Fuzzy C-Means as an unsupervised clustering method for overall feature vectors, then we applied linear discriminant analysis on the data (LDA) and finally we applied Neural Network classifier on different combinations of the extracted features. We found that the most significant features are: the white lines count, RTVTR. The ridge count has shown to have little significance, and slightly enhance the classification with the Neural Network classifier, while it degrades the performance of the Fuzzy C-Mean classifier. Adding any of the other least significant features to the input vectors result in degradation of performance of the classifiers.

Fuzzy C-Means (FCM) Clustering: By applying the FCM algorithm on the white lines count and RTVTR only as input features, a result of 80.39% classification rate was obtained and this result is shown as a confusion matrix in table 5. Adding ridge count to the previous two features, we obtained a degraded result of 56.47% classification as shown in table 6. It is shown in table 6 that adding ridge count to the feature vector highly decreased the classificationrate of males and slightly decreased the females' classification rate.

Linear Discriminant Analysis (LDA): By applying the Linear Discriminant Analysis on the white lines count and RTVTR, we got a result of 84.3 % classification rate for the testing set, as shown in the confusion matrix in table 3, with training error rate of 0.18. By adding the ridge count to the previous features, we got a result of 86.5 %, as shown in table 4, with error rate of 0.18.

RESULT

Average statistics along fingers for every pattern type was calculated together with different concordance and asymmetry properties for the corresponding fingers. The variation among females and males in the membership of the fingerprints to the different pattern types, and the average ridge count for fingers belonging to each pattern type, are very small, and thus are statistically insignificant. Male's and female's fingerprints are characterized by an average rightward asymmetry in the ridge count, i.e. the ridge count of a finger in the right hand is most likely greater than the ridge count of its corresponding finger in the left hand, but there is no significant difference in the degree of asymmetry between males and females, and thus the asymmetry is not a good candidate for the classification process. The pattern type concordance between left and right corresponding fingers doesn't show significant statistical variations between females and males. We found that the most significant features are: the RTVTR, and the white lines count averaged over the individual's 10 fingerprints, with the females having higher white lines count and RTVTR than the males. These two features have shown high significance in the classification process using FCM, and Neural Networks classifiers. Neural Network classifier has a higher classification rate than LDA. The average ridge count is slightly higher in males than in females, with high standard deviation among subjects of both genders. We found that adding this feature to the white lines count, and RTVTR slightly improves the performance of the classification process using Neural Network, and LDA, while it degraded the performance of the FCM classifier. Highest gender classification rate was 88% using Neural Networks and 86.5% using LDA. Gender classification results using these dominant features showed that this method could be considered as a prime candidate for use in forensic anthropology in order to minimize the suspects search list and give a likelihood probability value of the gender of a suspect.

Classification based on relative lengths of fingers and toes in human males and females: Digital scans of the hands and feet were obtained from 62 heterosexual females and 60 heterosexual males. Scans only of the hands were obtained from 29 homosexual females and 35 homosexual males. The lengths of the individual fingers and toes were estimated from those images by two experienced judges, and length ratios were constructed for all possible pairs of fingers (or toes) on each hand (or foot). Thumbs were not measured, but the great toe was measured and used to construct length ratios. Past research had concentrated on the relative lengths of the index and ring fingers (the 2D:4D ratio). This ratio is close to 1.0 in female and smaller than 1.0 in male. Here 2D:4D did exhibit the largest sex difference, for both hands, followed by 2D:5D and 3D:4D. The sex differences were larger for the right hand than for the left. For both homosexual females and homosexual males, nearly all of the length ratios for fingers were intermediate to those for heterosexual females and heterosexual males; that is, the ratios of homosexual females were masculinized and those of homosexual males were hypomasculinized, but few of these differences were significant. Because many toes were substantially arched, acceptable estimates of length often could not be obtained from the two-dimensional scans, meaning that conclusions about toes are much less certain than those for fingers. Nevertheless, the length ratios were generally larger for toes than for fingers, and the sex differences were generally smaller for toes.

Classification of gender from human gaits and faces: Computer vision based gender classification is an important component in visual surveillance systems. In this paper, we investigate gender classification from human gaits in image sequences, a relatively understudied problem. Moreover, we propose to fuse gait and face for improved gender discrimination. We exploit Canonical Correlation Analysis (CCA), a powerful tool that is well suited for relating two sets of measurements, to fuse the two modalities at the feature level. Experiments demonstrate that our multimodal gender recognition system achieves the superior recognition performance of 97.2% in large datasets.

A Component-Based Approach To Hand Verification

Introduction: The proposed system operates on 2D hand images acquired by placing the hand on a planar lighting table without any guidance pegs. The segmentation of the palm and the fingers is performed without requiring the extraction of any landmark points on the hand. First, the hand is segmented from the forearm using a robust, iterative methodology based on morphological operators. Then, the hand is segmented into six regions corresponding to the palm and the fingers using morphological operators again. The geometry of each component of the hand is represented using high order Zernike moments which are computed using an efficient methodology. Finally, verification is performed by fusing information from different parts of the hand. The proposed system has been evaluated on a database of 101 subjects illustrating high accuracy and robustness. Comparisons with competitive approaches that use the whole hand illustrate the superiority of the proposed, component-based, approach both in terms of accuracy and robustness. Qualitative comparisons with state of the art systems illustrate that the proposed system has comparable or better performance. Hand-based authentication is among the oldest live biometrics-based authentication modalities. The existence of several commercial hand-based verification 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 are not as distinctive as fingerprint or iris features. There are several reasons for developing hand-based authentication systems (Agnihotri *et al.,* 2006). 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.

System Overview: Figure 1 shows the main stages of our proposed system. The image acquisition system, shown in Figure 2(a)) consists of a VGA resolution CCD camera and a planar lighting table, which forms the surface for placing the hand. The direction of the camera is perpendicular to the lighting table. The camera has been calibrated to remove lens distortion. Figures 2 (b),(c) show some sample images acquired by our system. Under this setting, a fixed threshold is sufficient to extract a binary silhouette of the hand and the arm robustly. After image acquisition, the image acquired is 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 processed to segment the palm and the fingers. Feature extraction is performed by computing the Zernike moments of each part of the hand independently. The resulting representation is invariant to translation, rotation and scaling transformations. Finally, verification is performed by fusing information from different parts of the hand (Badawi *et al.,* 2007).

Fusion: This module fuses information from different parts of the hand to improve verification accuracy and robustness. In general, fusion can be performed at different levels. In this paper, we have experimented with three different fusion strategies: *feature level, score level, and decision level*.

Feature Level Fusion Using Principal Component

Analysis: The use of Principal Components Analysis (PCA) [**?**] for feature level fusion is quite popular. In this case, the feature vectors of the palm and the fingers are combined into a single feature vector. Then, PCA is applied to map them into a lower dimensional space. Essentially, each PCA feature represents a linear combination of the original features.

Decision Level Fusion Using Majority Voting: Majority voting is among the most straightforward decision level fusion strategies. In this case, the final decision is based on the output results of several matchers. In the context of hand verification, we verify the identity of a subject using each part of the hand (i.e., fingers and palm) separately. Then, if three or more parts of the hand support the same verification result, we accept this result as a correct verification; otherwise, we reject the subject.

Experimental Results: In order to evaluate our system, we have hand collected data from 101 people of different age, sex and ethnicity. For each subject, we collected 10 images of his/her right hand during the same session. Subjects were asked to stretch their hand and place it inside a square area drawn on the surface of the lighting table; however, no other restrictions were imposed on the subjects. To capture different samples, subjects were asked to remove their hand from the lighting table, relax it for a few seconds, and then place it back again. As a result, finger movement was unavoidable as shown in Figure 4(a). To calculate the distance between a query hand Q and

the template hands Ti of an individual in the database, we compute all Euclidean distances between the query and the templates and take the minimum distance:

$D = argimin\{||Q - Ti||\}, i = 1, .., k$ (3)

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 report our evaluation results based on the proposed hand-based verification system. First, we compare the different fusion strategies discussed earlier. Then, we illustrate the effectiveness of the hand decomposition scheme by comparing it with the approach of where the whole hand is used for verification without segmentation.

CONCLUSION

The proposed system decomposes the hand silhouette in different parts corresponding to the fingers and the palm and describes the geometry of each part using either boundary descriptors, based on FDs, or region descriptors, based on ZMs. To classify a given hand as male or female, it fuses information from different parts of the hand using score-level fusion and LDA. Although the dataset used in our experiments is rather small and all the data was obtained in the same session, we believe that the results presented in this study are quite encouraging. For future work, first we plan to perform more experiments using larger datasets. Moreover, we plan to investigate the issue of fusing boundary and region descriptors to further improve performance. Our experimental results in Section 6.1 indicate that ZMs and FDs provide complementary information. Second, we plan to evaluate the effect of time lapse on system performance. Third, we plan to evaluate the proposed system on populations of different ages. For example, an interesting problem would to investigate whether hand shape can be used to distinguish the gender of children. Finally, we investigate the benefits of integrating hand-based gender classification with hand-based authentication/identification.

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Fig 1. (a) Female hand image, (b) male hand image, and (c) segmented female hand image.

(a) (b) (c)

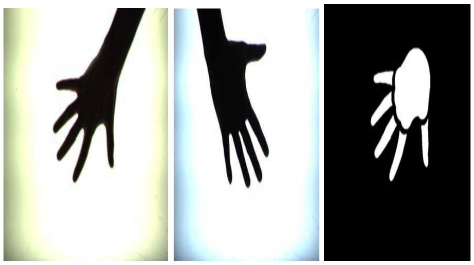

Fig 2. Sample images belonging to the same subject.

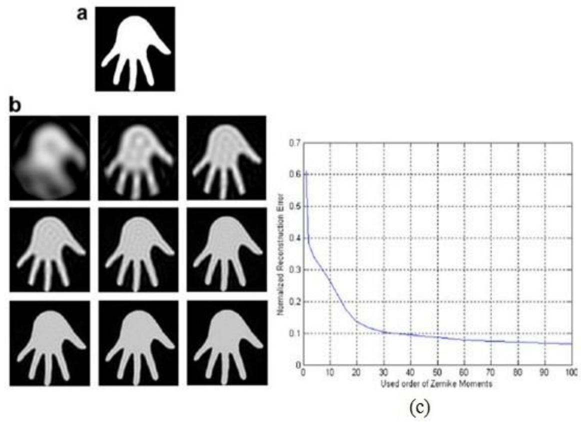

Fig 3. Original and reconstructed images with errors.

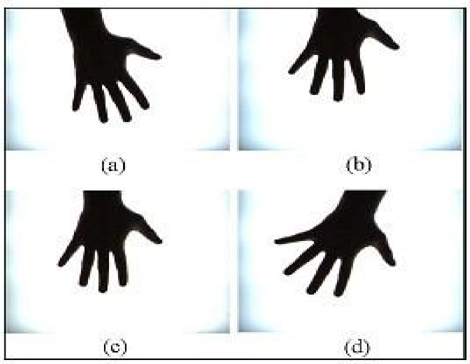

Fig. 4. Average ROC curves

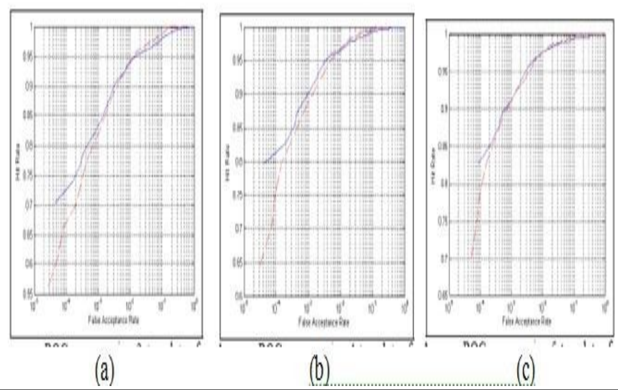

Fig 5. Two different fingerprints for a male showing no (or few) white lines and small RTVTR

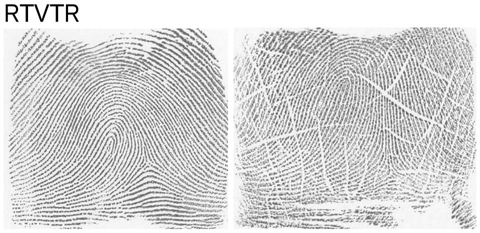

Fig 6. Two different fingerprints for a female showing large count of white lines and large RTVTR.

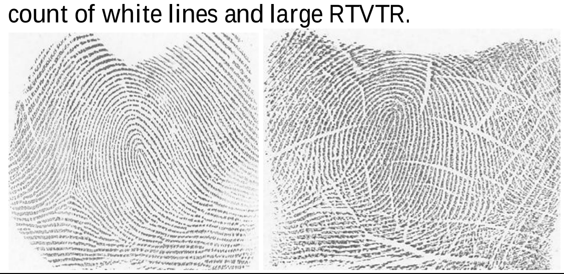

Fig 7. A male fingerprint, and (b) a female fingerprints.

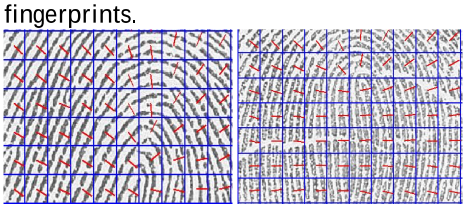

Fig 8. Block from (a) a male's fingerprint with RTVTR of 0.54, and (b) a female's fingerprint with RTVTR of 2.33.

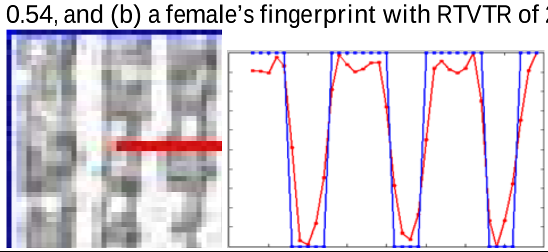

Fig 9: (a) Good, and (b) bad quality block, and their profiles.

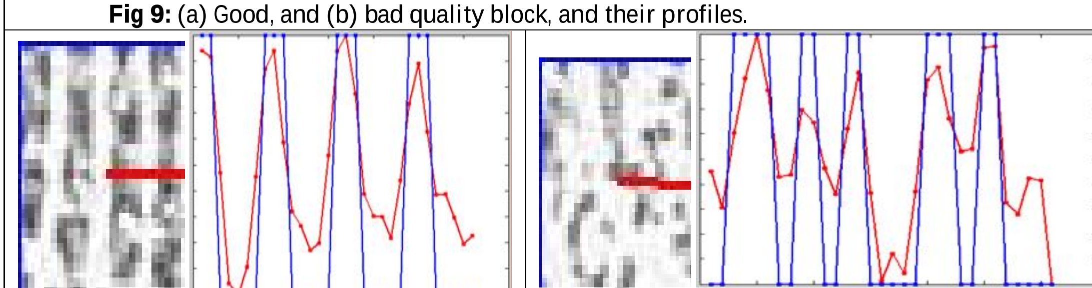

Fig 10. Block diagram of proposed system.

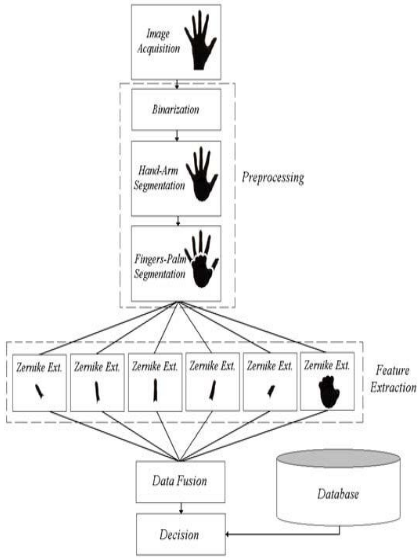

Fig 11. (a) Prototype image acquisition system, (b, c) images of the same hand.

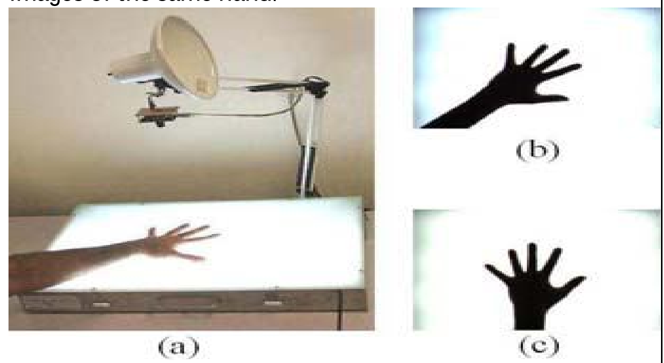

Table 1. Measurements (cm) of Hand Length in Males and Females (n=250).

Male	Minimum	Maximum	Mean	S.D.
➢ *Right*	15.30	21.00	18.89	0.88
➢ *Left*	15.40	20.80	18.90	0.87
Female	Minimum	Maximum	Mean	S.D.
➢ *Right*	14.80	20.40	17.22	0.92
➢ *Left*	14.80	20.40	17.22	0.93

Table 2. Measurements (Cm) of Hand Breadth in Males and Females (n=250) Hand index

Male	Minimum	Maximum	Mean	S.D.
➢ *Right*	7.30	9.40	8.45	0.40
➢ *Left*	7.20	9.40	8.42	0.40
Female	Minimum	Maximum	Mean	S.D.
➢ *Right*	6.70	8.80	7.48	0.38
➢ *Left*	6.60	8.70	7.42	0.37

Table 3. Age Wise Distribution of Hand Index in Males (n=125)

Age group (yrs)	Hand length (mean) in cm	Hand breadth (mean) in cm	Hand Index
18 to 19 (n=7)			
➢ Right	19.24	8.47	44.02
➢ Left	19.23	8.49	44.15
19 to 20 (n=28)			
➢ Right	18.89	8.51	45.05
➢ Left	18.95	8.49	44.80
20 to 21 (n=34)			
➢ Right	18.83	8.39	44.56
➢ Left	18.87	8.35	44.25
21 to 22 (n=38)			
➢ Right	18.99	8.51	44.81
➢ Left	18.98	8.48	44.68
>22 (n=18)			
➢ Right	18.64	8.33	44.69
➢ Left	18.61	8.31	44.65

Table 4. Age Wise Distribution of Hand Index in Females (n=125)

Age group (yrs)	Hand length (mean) in cm	Hand breadth (mean) in cm	Hand Index
18 to 19 (n=17)			
➢ Right	17.24	7.55	43.79
➢ Left	17.24	7.51	43.56
19 to 20 (n=40)			
➢ Right	17.29	7.47	43.20
➢ Left	17.29	7.42	42.91
20 to 21 (n=38)			
➢ Right	17.18	7.50	43.66
➢ Left	17.18	7.42	43.19
21 to 22 (n=23)			
➢ Right	17.10	7.43	43.45
➢ Left	17.12	7.37	43.05
>22 (n=7)			
➢ Right	17.37	7.48	43.06
➢ Left	17.36	7.40	42.65

Table 5: Confusion matrix for the FCM classification based on the white lines count, and RTVTR features.

Actual\Estimated	Males	Females	Total
Males	92	6	98
Females	13	55	68
Total	105	61	166

Table 6: Confusion matrix for the FCM classification based on the white lines count, RTVTR, and ridge count features.

Actual\Estimated	Males	Females	Total
Males	145	5	150
Females	45	60	105
Total	190	65	255

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