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Research Article

Palm and Finger Segmentation of High Resolution Images using Hand Shape and Texture

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Abstract: Amongst the diverse range of available biometric systems, hand based security system is considered as the oldest one. This paper focuses on dealing with high resolution images obtained from the HP scanner. The main advantage associated with this work is the ability to utilize the normal scanner for palm as well as for fingerprint acquisition so that the high cost associated with the palm and fingerprint scanner can be reduced. The proposed method is of significant importance since single image of hand is used to extract both the hand-shape and palm print. A robust methodology, based on fusion of contour and the texture approach has been proposed. To capture the contour of the hand, B-Spline curve has been used. Whereas, for the texture based approach Fourier transform followed by edge detectors has been employed. In order to attain the better accuracy of detection, HOG (Histogram of Oriented Gradients) descriptor is used for feature extraction.

Keywords: Hand based system, high resolution images, segmentation, biometric systems, palm-print.

1. INTRODUCTION

Personal authentication has gained much importance in the current information systems, including access control in confidential areas, electronic payments, securing computer's or smart phone's data, etc. Amongst the other developed systems, biometrics has played a vital role for the security purposes [1]. The commonly measured traits are fingerprints, hand shape, gait, palm-print, face, voice, etc. Amongst the other existing biometrics, human hand is considered as the oldest technology [2] and it has gained researcher's attention because of its permanence, uniqueness and reliability [3]. Palm print, hand vein, knuckle point, fingerprint and hand geometry are usually extracted from hand. These features are reliable and stable throughout the life span, after a person reaches his adulthood [4]. At this time, mostly the acquisition devices are working on low resolution and some of them use pegs or guidance peripherals for the image acquisition [5, 6].

Most of the previous work in this field has been done on the low resolution images. This paper focuses on dealing with high resolution images obtained from the HP scanner. Thus, cutting off high cost associated with the palm scanners. This paper proposes a novel approach to segment out the whole hand into palm and fingers without extracting any landmark points or using pegs.

The several steps involved in the development of proposed method are as follows: First, utilize the hp scanner for hand scanning. Secondly, in order to deal with different posture of hand, it was decomposed into palm and fingers. Third, the landmark points were avoided because the finger valleys are not reliable for different poses of hand. Finally, instead of traditional approaches

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used for the representation of hand geometry using geometrical measurements, geometry of all parts of a hand like palm and the fingers are represented separately. With the intentions of avoiding the touching of the fingers, users should stretch their hand slightly during scanning.

2. RELATED WORK

In literature, many approaches have been proposed for the palm-print and fingerprint recognition purposes. Early studies employed the peg based systems to provide assistance for the placement of user's hand [7, 8]. It is not user friendly as well as unreliable since pegs can deform the image severely. Mostly palm-print databases were background restricted [5]. Jain et al. [9] and Oden et al. [10] used hand image taken at low resolution as well as the pegs to restrict the movement of hand. The obtained results were quite promising. Recently proposed contact-less palm-print systems have used monotone dark backgrounds to avoid the segmentation [11]. Palm segmentation plays a vital role in system's performance, since better segmentation results can lead to better selection of region of interest (ROI) thus, increases the recognition rates [12]. Neves et al. [13] presented a biometric identification technique using palm image. Through the identification of human palm using the textural and geometrical data obtained from the Local Binary Pattern (LBP) method, a Palm-Print Authentication System (PPAS) was implemented, the approach was tested on 50 images and the results were quite effective. Afsal et al. [14] used the fuzzy entropy to calculate the maximum uncertainty in the information. It uses fuzzy function to extract the maximum possible information from the palm images, since it is full of uncertainties.

Using detection techniques based on skin color, segmentation can't be done in cluttered environment because of same chrominance values. Multimodal systems have attracted the attention of the researchers. Recently [1, 15-17], have developed some techniques for the implementation of multimodal systems. Zhu et al. [18] proposed a multi-modal system based on palm-print, knuckle point, finger geometry, and features by fusing them at decision stage to enhance the efficiency of the matching module along with the accuracy of recognition. G. Amayeh et al. [19] segmented the hand using a tough, iterative procedure by utilizing the morphological operators. They employed Zernike moments for the representation of the geometry of each segmented part. Afterwards, the hand image is separated into 6 sections i.e. palm and the finger's region. Higher order Zernike moments are used for the representation of geometry of all parts of hand. Feature extraction using the landmarks has been very successful but it needs a reference image for comparison of detected landmarks with the reference landmarks [20]. Some researchers employed Component-based approach using region descriptors comprises of high order Zernike moments for hand-based verification and identification [21] to improve efficiency and speed, along with the ease of use. Wu et al. [22] used hierarchical method to develop the feature vectors taken from centroids of various areas of hand. The quality of hand image was not so satisfactory and it was affected by the illumination device which can also affect the accuracy of the system.

Geometric metrics like length, width, Euclidean, and weighted Euclidean have been used for the feature extraction, but these methods are not so efficient because they are more prone to errors [23]. Rahman et al. [24] proposed a new hand approach based on the geometry, using Distance-based Nearest Neighbor (DBNN) algorithm and the Complete Graph Theory (CGT). Han et al. used the NIR camera and NIR LEDs in which segmentation is considered as a part of hardware [25]. Wang [26] implemented a technique using both hand-tracking and gesture recognition on FGPA using combination of YCbCr color space and region growing algorithms, including morphological operations for the noise removal. Another novel approach based on scattering wavelet transform (SWT) was proposed by Saranraj et al. [27]. They extracted the discriminative features from the palm image that were considered most useful in the matching process, then simple Euclidean distance based matching was employed.

Comparing the methods of visible light with the approaches using infrared light [28], the results show that the latter performs well. The method employed by Morales et al. [28] improved the performance of image acquiring device, but it raises another flaw in it. They used a template of palm to assist the users in placing their hand on the image acquisition device; it reduces the flexibility of hand along with the practical application of hand based verification system.

Kumar et al. [29] used the combination of palm print and the hand shape signature to develop a peg free recognition system, but their computational cost was quite high. An ordinary flat-bed scanner was used for the image acquisition, user could place its hand freely and naturally on the scanner. Amayeh et al. [30] developed an approach by employing a simple lighting table and a VGA (video graphics array) resolution CCD camera, without involving pegs. The camera was directed perpendicular to the direction of the table. It produces a binary, noise and shadow free image of hand. Sato et al. [31] pointed out the problem of extraction of the exact palm-region from the images with large deformation, using a contact-less palm recognition method. They proposed a system using 3D measurements with diffraction grating laser. Aishwarya et al. [32] presented a novel system that detects the bio-metric traits utilizing the liveness detection method and the weber's local descriptor algorithm; thus reducing the spoofing methods, simply employing the Euclidean distance formula both false acceptance and false rejection rates are reduced.

The paper proceeds as: the image acquisition device and pre-processing steps are discussed in section 3. Then section 4 analyzes the active approach suggested in the paper, by proposing a robust approach comprises of the fusion of geometrical features and the texture of hand. In section 5, the extraction method for palm and fingers is described. Section 6 includes the presentation of the results on the new hand database along with its comparison with other existing techniques. In the end, section 7 concludes the paper with a brief dialogue along with the suggested future work.

3. IMAGE ACQUISITION AND PRE-PROCESSING

To confirm the validity and efficiency of the proposed technique, a new database has been developed. For this purpose, a normal high resolution scanner has been used as shown in Fig. 1. Images at the resolution of 1200 ppi have been taken from this device. Images are captured by placing the hand on the scanner with the fingers stretched. No guidance assembly like pegs is used to restrict the placement of hand on the device. Size of images obtained at the resolution of 1200 ppi (pixels per inch) is 7,000 × 6000 pixels.

Fig. 1. HP scanner used for hand scanning.

Some samples of hand captured from the high resolution hp scanner are given in Fig. 2. Since, the imaging is peg free, thus, it is accepted by the public easily. To decrease the computational cost of the system the size of the image is reduced to 1800 × 1300 pixels and later on, restored to its original value.

Pre-Processing

Images taken from the scanner need some preprocessing steps to make them more feasible for use. First, the images are converted into grey scale by Eq. (1) [18].

$$\boldsymbol{G(row,col) = 0.587 * C_{Green}(row,col) + 0.299 * C_{Red}(row,col) + 0.114 * C_{Blue}(row,col)} \quad (1)$$

where C_{Green} (row, col), C_{Red} (row, col), and C_{Blue} (row, col) are used to show the color constituents of green, red, and blue, respectively.

In order to enhance the contrast of the images, contrast stretching is used. The equation governing this process is given in Eq. (2).

$$I_{Norm} = (I - I_{min})\frac{I_{newmax} - I_{newmin}}{I_{max} - I_{min}} + I_{newmin} \quad (2)$$

4. PROPOSED WORK

A segmentation algorithm has been proposed here, that can extract as well as utilize the palm-print and fingerprint at the same time. Segmentation of hand

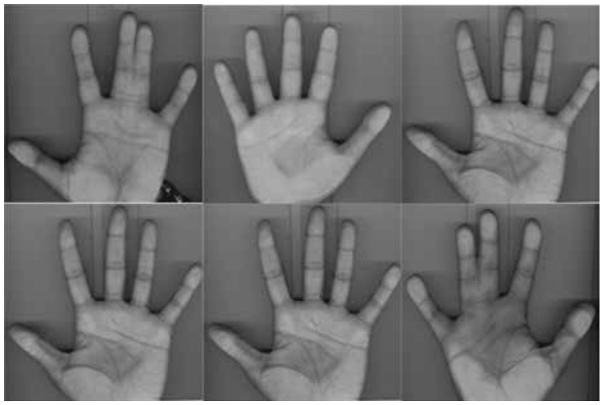

Fig. 2. Images form database scanned by hp scanner.

into its different regions can be made robust by sensing the landmarks on the silhouette of hand, but this approach is more susceptible to errors. Thus the overall efficiency of the system is reduced. The proposed methodology is given in Fig. 3.

4.1 Texture Based Approach

Texture based approach is implied to separate out the background from the hand image. It involves the following steps: First, the Fourier transform of enhanced image is calculated. It helps in determining the frequency components of image. Through visual inspection, it is found that there exists a certain band of frequencies which correspond to the desired part of the image. Therefore, Gaussian Band-pass filter has been applied on the transformed images to extract the band of frequencies which are suitable for the enhancement of image. It helps in making the outer boundary of the hand noticeable by removing the undesirable frequency components from it.

Since the image is 2D so there is a need to use the two 1D Gaussian functions, as given by Eq. (3).

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{\frac{x^2+y^2}{2\sigma^2}} \tag{3}$$

Afterwards, there is a need of a threshold value, that can be used effectively and efficiently to separate the desired area from the background.

In order to get the adaptive threshold value for the pixels of the image that are outside the hand silhouette i.e. the background pixels, an analysis is performed. Since in the generalized automatic system, it is required to extract the region of interest from a huge number of databases. The value of the threshold relies upon the intensity values of all pixels, and then the best value is chosen as the threshold. For this purpose many techniques have been used like histogram. But Otsu's [33] method for threshold has proven itself a good candidate for the choice of a threshold value. Since this method assumes that the image belongs to two pixel classes i.e. foreground and the background, it computes the best threshold value that separates the two classes such that their intra-class variance is insignificant. The pseudo code for Otsu's method for threshold is

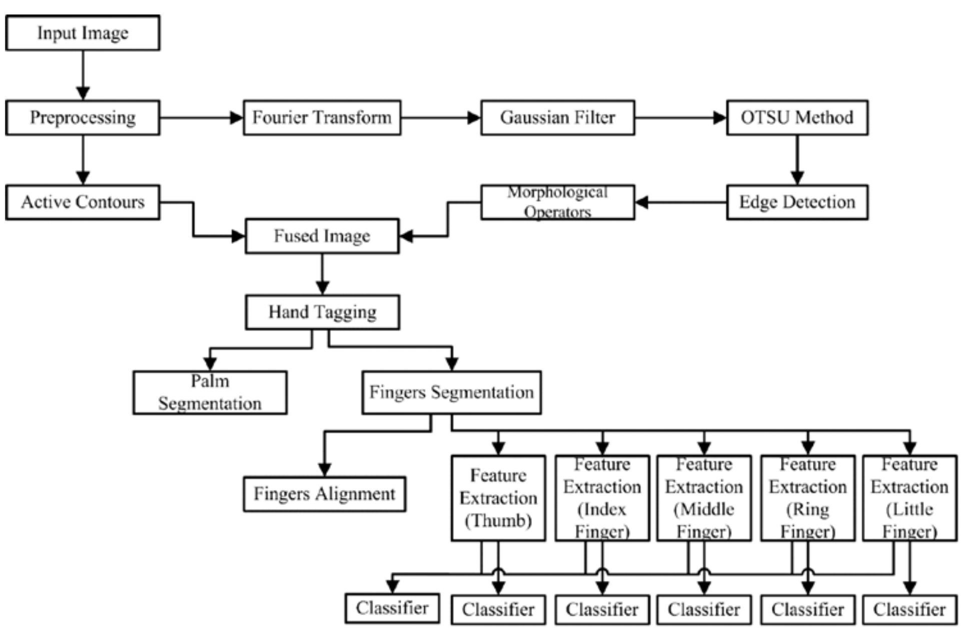

Fig. 3. Proposed algorithm for palm-print and fingerprint segmentation.

given in Table 1.

Table 1. Otsu algorithm for thresholding.

Otsu's Algorithm Pseudo code
1. Compute the histogram and the pixel counts for each level of intensity. 2. Initialize ω_i and μ_i 3. Go through all possible thresholds T=[0,255]. 4. Update ω_i and μ_i 5. Compute $\sigma_i^2(T) = \omega_1(T) \cdot \omega_2(T) \cdot [\mu_1(T) - \mu_2(T)]^2$ 6. Required value of threshold is the maximum value of $\sigma_i^2(T)$.
$\omega_i(T)$ = Number of pixels in class i $\mu_i(T)$ = Mean pixel intensity in class i $\sigma_i^2(T)$ = Inter class variance

After making the choice of the threshold value, sobel edge detection operator is convolved with filtered image (that contains the certain band of frequencies) to obtain the hand response in horizontal, vertical and diagonal directions, shown in Eq. (4). The edges obtained from it generally correspond to the wrinkles and shape of the hand. To eliminate the little bogus borders from the background of the hand silhouette, the edged image needs smoothening.

$$G_{hor} = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}, \quad G_{vert} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix},$$
$$G_{dia\_pos} = \begin{bmatrix} 0 & 1 & 2 \\ -1 & 0 & 1 \\ -2 & -1 & 0 \end{bmatrix}, \quad G_{dia\_neg} = \begin{bmatrix} -2 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 2 \end{bmatrix} \quad (4)$$

where $\boldsymbol{G_{dia\_pos}}$ and $\boldsymbol{G_{dia\_neg}}$ are at -45 and +45 respectively. To remove the unwanted edges and the borders from the image, morphological operations like erosion, dilation, opening and thinning with structuring element given in Fig. 4 are applied to provide the best solution. They remove the spurious objects as well as fill the gaps present in the image.

1	1	1
1	X	1
1	1	1

Fig. 4. Structuring element used for morphological operations.

4.2 Geometric Based Approach

Although threshold value selected from Otsu's method is giving satisfactory results but for some images, it is unable to find all parts of hand. Figure 5 shows the resultant image after applying the threshold and the morphological operators, some fingers are not segmented correctly due to the similarity of their pixel values with the background. Hence, use of Snakes as an active contour model has been introduced to extract the silhouette of hand. Therefore, remaining parts of the hand can be filled accurately. This method encompasses two stages, namely, Snake based Background Removal (SBR) and Snake based Hand Localization (SHL). SBR is employed to remove the background from the image whereas SHL is used for the localization of hand silhouette.

Generally, the basic goal of most active-contour algorithms is the extraction of a homogeneous region in an image, whilst the goal of most anisotropic-diffusion algorithms is the smoothening of the values within the homogeneous region, not across the boundaries. The most widely used mathematical models addressing both goals

Fig. 5. Incorrect segmentation results.

is of Mumford and Shah [34-35], they proposed a variation problem of minimizing a function that includes a piece-wise smooth model of an image. The proposed function incorporated a geometric term, penalizing the Hausdorff measure of a set in which certain discontinuities would be acceptable.

The basic concept behind the evolution of active contours is to reduce the difficulty encountered during the adjustment of a contour while using the explicit representations, for example chain codes. Since, these explicit representations don't provide the susceptible computational manipulations results, therefore active contours (in two dimensional space) has been defined in the form of rectangular mask, to get the required contour, in this case its hand. This approach helps in the segmentation of those images having homogeneous but statistically different foreground and backgrounds. The active contour C_i is defined by Eq. (5).

$$C_i = \{(r, c) \epsilon R^2 | \phi(r, c) = 0\} \tag{5}$$

where, Φ defines a scalar field when the level set of active contours is zero. After initializing the contour, C_i ceases to modify itself. In this way, the difficulty of adjusting C_i to the data input (here, it is the hand image) stops to modify Φ, so there is a need to define the Signed Distance Function (SDF) for Φ which assigns negative sign to Φ when the mask is in the inner side of the contour as shown in Eq. (6):

$$\phi(r, c) = (-1)^{I(r,c) \epsilon \operatorname{int}(C_i)} \min \| (r, c) - (r', c') \| \tag{6}$$

where $\operatorname{int}(C_i)$ shows the interior of the contour and || is the sign function. Hence, it becomes as Eq. (7)

$$\phi(r, c) < 0 \leftrightarrow (r, c) \epsilon \operatorname{int}(C_i) \tag{7}$$

Active contours, without edges have been implemented in this paper, proposed in [36]. It is constructed by using the curve evolution techniques, segmentation function of Mumford and Shah [34-35] technique and the level sets. It has ability to detect those objects which doesn't contain the strong gradient at the boundaries. It has the advantage that the problem of minimal partition in the formulation of level set becomes the mean curvature flow problem. Thus, stops the evolution of contour at the desired edge. Another advantage of this approach is that the initialization of initial curve doesn't affect the efficiency and it automatically detects the interior contour.

Active contours integrates the information of local-adaptive neighborhood image with the help of adapted spatial morphological opening and closing operations utilizing general neighborhood structuring elements. Incorporation of the general adaptation in local-neighborhood information resulted in the robustness of active contours model to the non-uniformity. It also helps in the solution of the minimized energy function through morphological approximations, thus increasing the stability and the contour evolution speed. Consequently, a general spatially adapted information combining morphological active contours without edges are generalized, i.e., prone to non-uniformity and noise and there is no need of re-initialization. The resultant images after the application of active contours are shown in Fig. 6.

4.3 Fusion Process

Similar to the texture based approach, geometric based approach is susceptible to some errors, like the fingers are not completely segmented from the hand and also the finger tips are not segmented correctly. Therefore, there is a need to fuse the results obtained from the region based and the geometrical features. The fusion is done by using the logical OR operator using Eq. (8).

$$I_{fusion} = I_{texture} \,||\, I_{geomerical} \tag{8}$$

It helps in combining the both results. The resultant fused image is given in Fig. 7. A robust methodology is needed to separate the palm and the fingers from the hand image.

4.4 Hand Classification

Hand can be classified as left or right by extracting four points from it. All of the extracted points are the tips of fingers. An algorithm described in section 5.2 can be used for the determination of correct peak points. The proposed system is quite flexible since it allows the user to use both hands. The detected hands can be stored separately in the database which reduces the searching database to

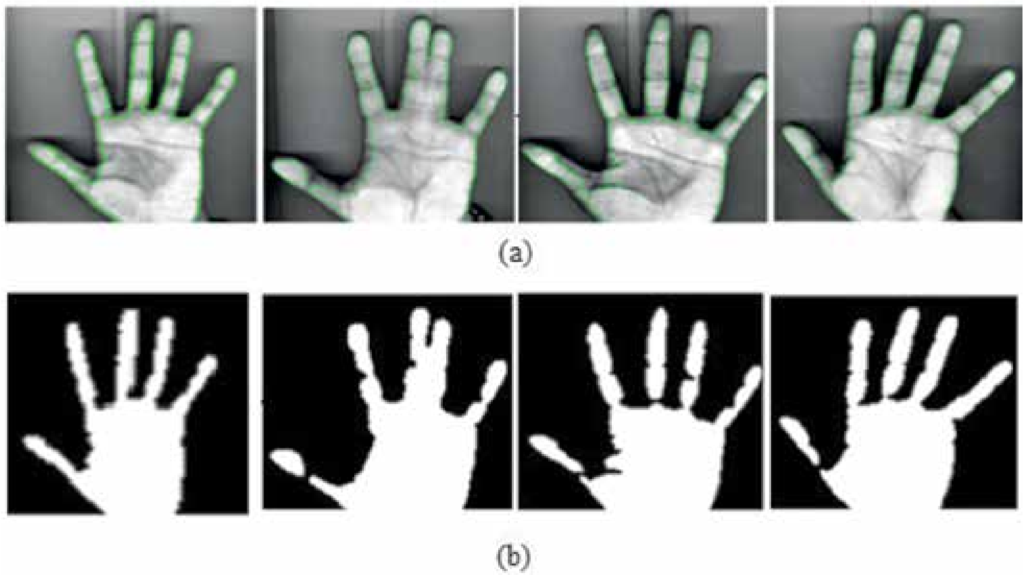

Fig. 6. Segmented images using active contours: (a) Detected boundary images; (b) Resultant segmented images.

half, thus speeds up the recognition process. Fig. 8 shows the fingertips of left and right hand.

Eqs. (9) and (10) are used for the classification of hand.

Left hand determination:

$$x_1 > x_2 AND x_1 > x_3 AND x_1 > x_4 AND x_1 > x_5 AND y_1 < y_2 AND y_1 < y_3 AND y_1 < y_4 AND y_1 < y_5 \quad (9)$$

Right hand determination:

$$x_5 > x_1 AND x_5 > x_2 AND x_5 > x_3 AND x_5 > x_4 AND y_5 > y_1 AND y_5 > y_2 AND y_5 > y_3 AND y_5 > y_4 \quad (10)$$

where, x_1 to x_5 are the horizontal coordinates and y_1 to y_5 are the vertical coordinates of the fingertips.

5. PALM & FINGERS SEGMENTATION USING PROPOSED ALGORITHM

5.1 Palm Segmentation

Palm is the source of abundant information and the complex part of hand. Mostly researchers have used the algorithm which searches for the maximum inscribed circle in the whole image and then by drawing the rectangle around that circle the palm region is separated [18]. Although this is an effective method for the palm detection, but this approach has a drawback associated with it, that it is much time consuming. Since the circle modifies itself again and again it raises the computational cost of the overall system. Therefore, with the propose

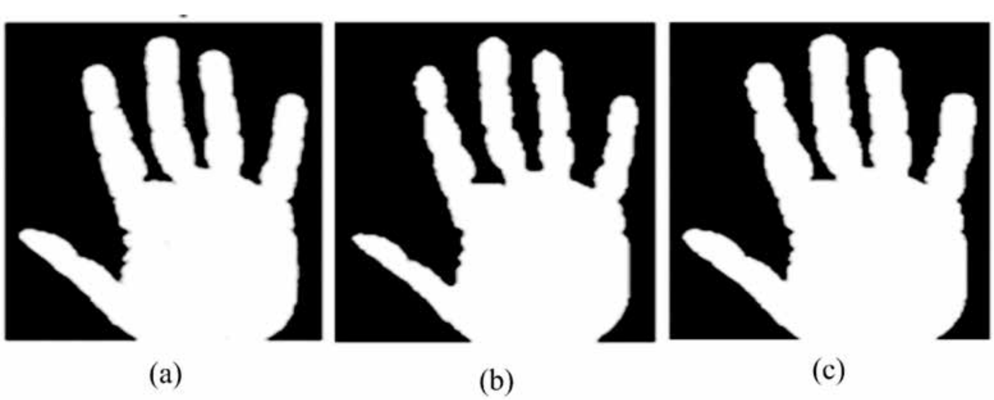

Fig. 7. Fusion process: (a) Resultant image obtained from texture based analysis; (b) Active contours result; (c) Resultant fused image.

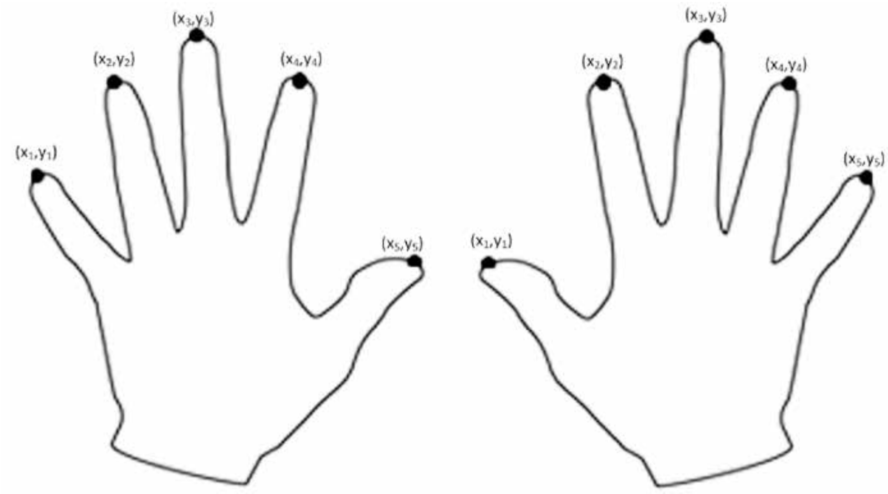

Fig. 8. Right and left hand fingertips.

method for improving the processing speed of the algorithm, the palm is segmented from the whole hand by detecting the largest finger valley point. The valley points are calculated using Eq. 11.

$$v_k = argmin\,(\,||\zeta - h_c||\,) \tag{11}$$

where, $\zeta = c(f_n, f_{n+1})$ is the portion of edge from finger-tip f_k and f_{k+1}, with n = {l, r, m, L} that means little, ring, middle and index finger and h_c is the contour of hand [37]. The palm extracted from the image along with the bounded box is shown in Fig. 9.

5.2 Fingers Segmentation

After separating the palm region from the whole hand, the remaining part of the image comprises of fingers. There is a need to separate theses fingers from each other. Thumb can be easily separated from the other four fingers as it is not connected to any of them. Thumb is removed from the image by assigning it a different label and then separating that particular label from the image. The separation of other four fingers from each other is a tricky job. For that purpose again finger valley points have been searched throughout the image. The valley point is the area where the y coordinate of the image first decreases and then increases in its magnitude. The approach used here for locating the valley points is to find the minimum sum in the vertical direction and then on that particular column a search window of 100 pixels is employed. It searches for the exact valley point by starting from the x-100 coordinate to x+100. If the searched area has the property that the y coordinate first decreases then increases the inflexion point is chosen as the valley point. The required point can be found easily and accurately because the segmented image with sharp edges has been improved by the morphological operators. Finally, on the basis of these valley points the fingers are separated from each other. The image after the removal of palm is given in Fig. 10 (a) and

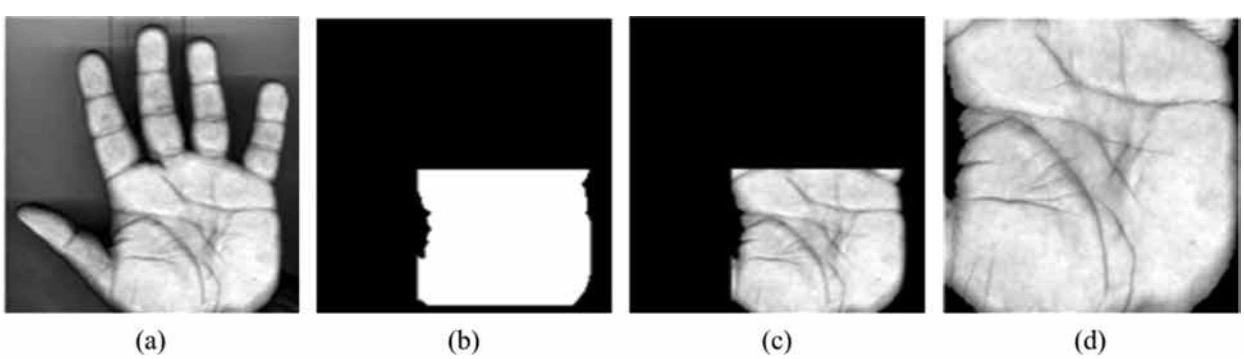

Fig. 9. Palm segmentation: (a) Pre-processed image; (b) Extracted palm; (c) Segmented palm from pre-processed image; (d) Bounded box of palm.

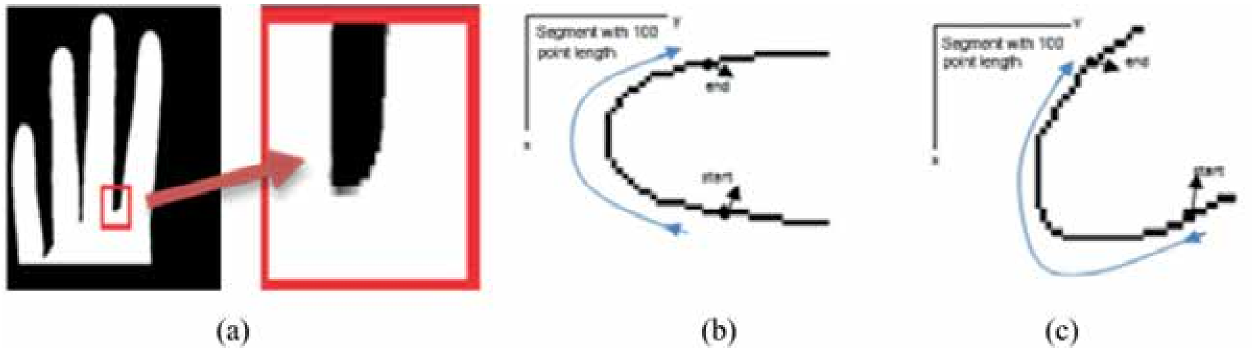

Fig. 10. Fingers and Valley point Detection Scheme: (a) Fingers and valley point; (b) and (c) Valley-point detection scheme for different postures of hand.

the search process examples are displayed in the Fig. 10 (b) and (c). Figure 11 shows the segmented fingers using proposed method.

Afterwards, there is a need to tag these fingers i.e. thumb, middle, ring, index and little finger. To do this, geometrical features of fingers must be calculated. These features can be length, width, and variance of width, orientation, variance of orientation and the angular distance amongst the fingers. The better the features, the better will be the classification.

5.3 Feature Extraction

Feature extraction involves the process of extracting the features detail from the image. The geometrical features of hand include finger length, area, curvature, thickness, and width. The Histograms of oriented Gradient (HoG) is an alternative method to encrypt the image to find visual descriptor's vector. The examples are Lowe's SIFT [38], Dalal and Triggs' HoG [39], Berg's geometric blur and shape context [40], and Riesenhuber and Poggio's C1 [41]. Histogram of Gradients feature (HoG) parameters are much more appropriate then the SIFT feature, for generic object identification. HoG consists of the Scale Invariant Feature Transform (SIFT). It uses the orientations and the magnitude of gradients around the critical locations to compute the histogram of these points. It is defined as a weighted histogram in which each bin of histogram assembles the sum from the gradient points of the particular location having the particular orientation. The image gradient is computed using 1D discrete derivative kernel in both the vertical and the horizontal directions, the kernels are given in Eq. 12. [39].

$$[-1\ 0\ 1]\, and\ [-1\ 0\ 1]^T \tag{12}$$

The magnitude and the corresponding orientation of each pixel is given in Eq. 13 and Eq. 14.

$$g_{mag}(x,y) = \sqrt{g_x^2(x,y) + g_y^2(x,y)} \tag{13}$$

$$\theta(x,y) = tan^{-1}\left(\frac{g_y(x,y)}{g_x(x,y)}\right) + \frac{\pi}{2} \tag{14}$$

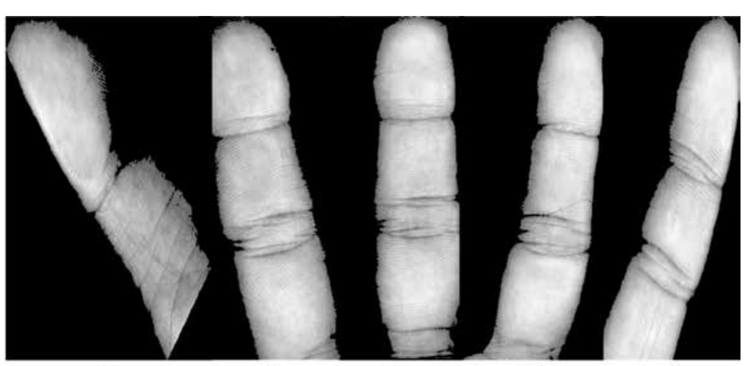

Fig. 11. Segmented fingers: (a) Thumb; (b) Index finger; (c) Middle finger; (d) Ring finger; (e) Little finger.

where g_y (x, y) and g_x (x, y) are gradient values in the vertical and the horizontal direction, respectively. The total numeral of bins present in the histogram of image are used for the quantization of orientations (nine orientations in this case).

The cells are grouped into blocks to normalize the strength against various contrast and illumination. These blocks overlap with one another, thus each bin is contributing its orientation more than once. In every block of histogram, the sum of all magnitudes in a particular direction is computed. To normalize these histograms, histogram is divided by the total sum of all orientations using Eq. 15, so that a normalized value between 0 and 1 can be obtained.

$$f_i = \frac{v_i}{\sqrt{||V_i||^2}} \tag{15}$$

$F = \{f_1, f_2, \dots, f_n\}$ is the resultant HoG feature vector. The feature set of HoG comprises of the histograms constructed inside a rectangular section on the given input image. The toolbox used for the implementation of HOG is VLFEATROOT [42]. Fig. 12 shows the results of HoG.

5.4 Orientation

The orientation of each finger of the hand is different from each other. To align all the fingers in a particular direction, further processing can be carried out from them. Since the device used for the image acquisition does not use any peripheral devices therefore, the fingers can have any orientation in any direction.

In literature, many approaches have been presented for the alignment of the orientation of hand and fingers. In this case, the image can only be acquired in a particular direction, there is no need to take into account the orientation of hand. Kumar et al. [43] used an inertial matrix to find the large Eigen value corresponding to the ellipse's main axis that fits into the region of hand. Another technique uses the hand silhouette of the binary image for the application of chain codes. Both the hand valleys and the finger tips are extracted and on the basis of the middle finger's key point a rotation process is performed. It gives the maximum angular variation of only 20%. Therefore, it is not a good method to be used in the unpaged system.

The method used for the alignment of fingers in literature is 'Image registration' in which the central finger or any pre-defined finger from the database is used as a base and all the other fingers are aligned according to that finger. In this case, since the size of the image is quite large and the image registration process cannot be carried out as it increases the computation cost of the system. For this purpose, first the orientation of each finger is found by the orientation finding method of image cropping, then on the basis of values of orientation, a search process is used that aligns the fingers in the erect direction, The orientation of each finger is found with respect to the x-axis. The resultant and the original orientation of fingers are given in Fig. 13. The contour of each finger is rotated by using Eq. 16.

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{16}$$

Where, x and y are the central co-ordinates of the contour of finger. The orientation alignment is used i) to extract the finger tips easily ii) to obtain the fingerprints region.

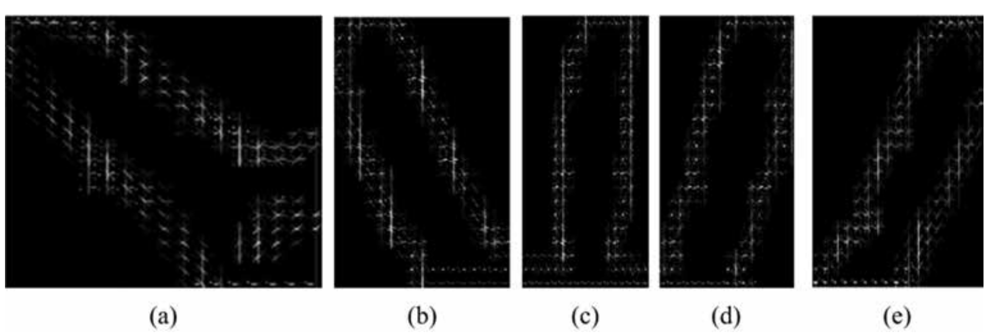

Fig. 12. HOG on binary images: (a) Thumb; (b) Index finger; (c) Middle finger; (d) Ring finger; (e) Little finger.

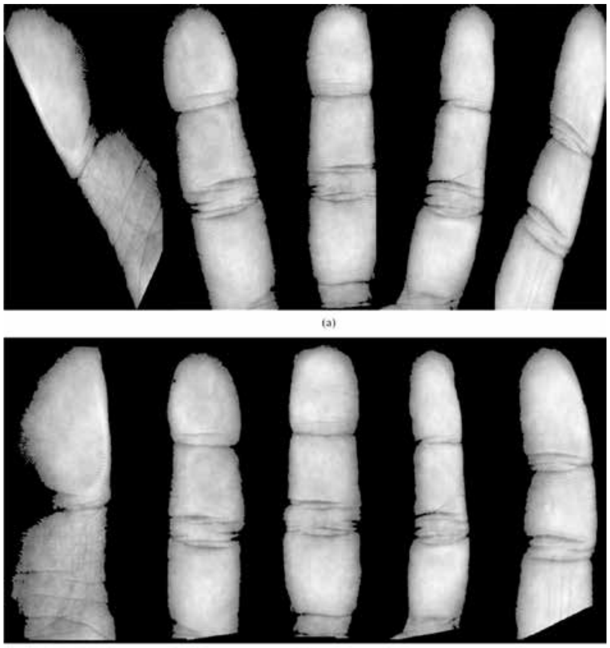

Fig. 13. Fingers alignment: (a) Original orientation; (b) After alignment using HoG.

6. RESULTS AND DISCUSSIONS

6.1 Error Rate Analysis

In this paper, we used k-NN classifier for the decision making that whether the finger is classified correctly or not. The features are distributed using the k-NN classifier, which operates on a non-parametric method for the classification and regression. It employs the minimum Euclidean distance among the test feature vectors and all other sample training data. In the regression stage of k-NN classifier, the output value is taken by averaging the values of its *k*-nearest neighbors.

On the basis of this classification, False Acceptance and False Rejection error rates are computed. The error probabilities are denoted as: P (FAR) and P (FRR).

The total probability of FAR is the given in Eq. 17.

$$\text{P (FAR)} = \prod_{i=1}^{n} P(FAR) \qquad (17)$$

where, P (FAR) is the probability of a False Accept Rate. Similarly, for the False Reject Rate (FRR) is given in Eq. 18.

$$\text{P (FRR)} = 1 - \prod_{i=1}^{n} (1 - P(FRR)) \qquad (18)$$

where, P (FRR) is the probability of a False Reject rate.

6.2 Experimental Results

To validate the results of this research, database of 100 persons was collected. The database consists of 400 hand images, four images per person, obtained from the high resolution HP scanner at the resolution of 1200 ppi, using peg free arrangement. The hand images were collected from the persons of age between 16 to 55 years. The image acquisition process was carried out while making sure that 1) The fingers are far apart from each other and 2) the upper lid of the scanner is closed. The automatic segmentation of palm and fingers was achieved through proposed algorithm discussed in Section 4.

Palm is separated from the image, only fingers are used for the classification purpose. The reason behind its usage is to tag the fingers. The size of the fingers, in the image, is reduced to 600 × 500 pixels. Thus, HoG can be applied effectively and efficiently. The size of the feature vector obtained is 10,540 × 1. The subjects were trained on the basis of these feature vectors and the classification was done using 2 out of 4 images as a database images whereas the other 2 images are used for the classification to increase the identification rate. It allows the fair combination by using the same training and test data. All the reported experimental results are carried out using Matlab. The system used is Intel Atom, Dual Core CPU, 1 GB RAM, 500 GB HD and Windows 7(32 bit) operating system.

Figure 14 displays the identification rate with respect to the various numbers of fingers extracted from the images present in the database, the range of images varies from 1 to 400. The inspection of the identification rate curve shows that results better than 96.9% can be achieved by increasing the database size. Figure 14 helps in determination of the accuracy with which each finger is classified by k-NN classifier.

The accuracy of detection of each finger is shown by a bar graph given in Fig. 15, whereas, ROC of all fingers and of each finger separately is plotted in Fig. 16 and Fig. 17, respectively.

Table 2 shows the performance of the proposed

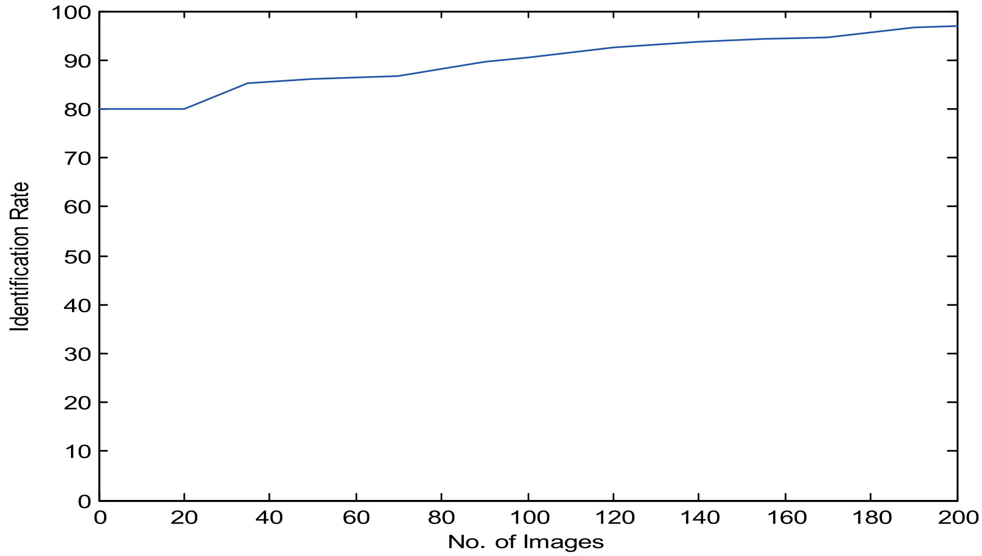

Fig. 14. Identification rate

method. It validates that the proposed solution can perform well in the given scenario. Hence, it can control the access privileges on a large scale. The previous results show that the image quality effects the identification rate. Since the device used here provides the high resolution images thus there is no flaw in the system due to image quality.

The Equal Error Rate (EER) of each finger is separately given in Table 3, whereas the comparison with other existing techniques is given in Table 4.

Table 2. Performance properties.

Performance Properties	
Total images	400
Identification Rate	96.9%
FAR	0.0309
FRR	0.0312
EER	0.0311

7. CONCLUSIONS

A bi-modal biometrics system, based on the features of hand, has been proposed. The proposed scheme combines the efficacy of hand geometry and the palm prints with the high precision of fingers geometry. The results of the geometric and texture based approach are combined at the fusion stage to segment out the hand image. Since the segmentation process includes the separation of palm and fingers from the hand image, hence their features are not related to each other. For further study these feature vectors has been implemented independently to increase the system performance. The features extracted from the fingers can be

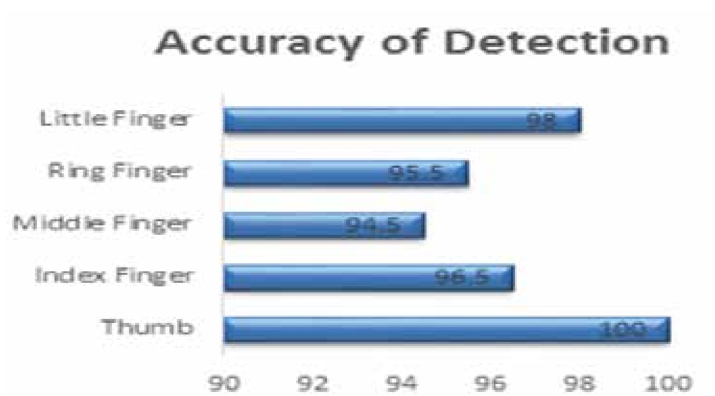

Fig. 15. Graph representing the accuracy of detection of each finger.

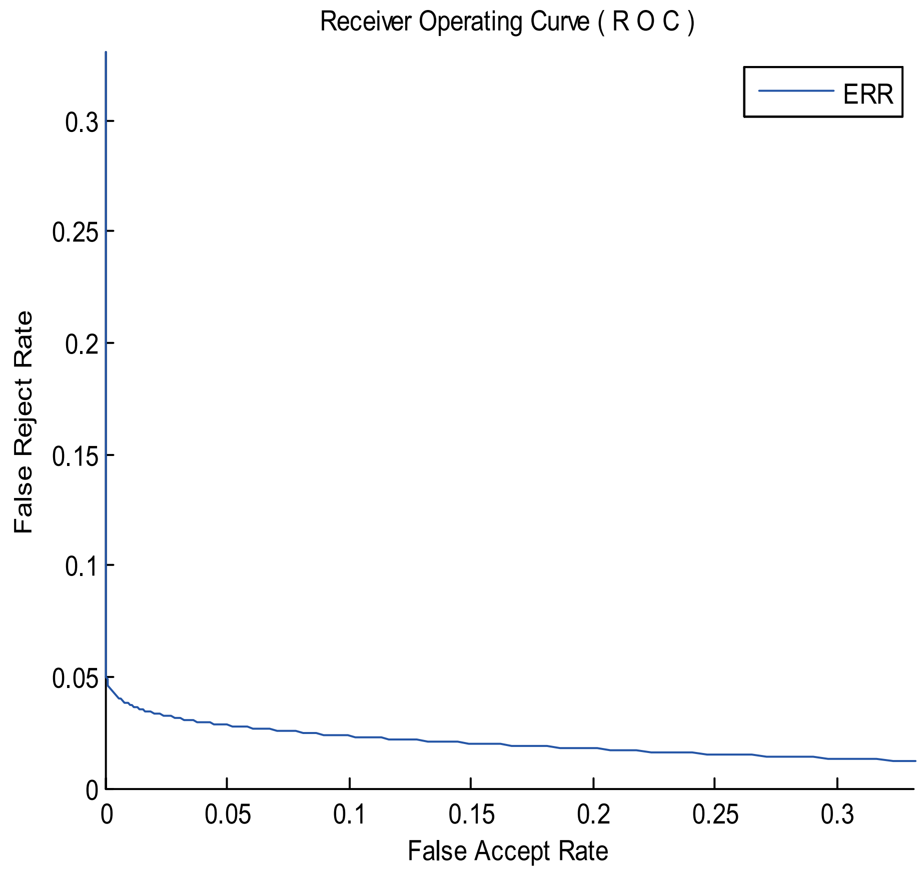

Fig. 16. Receiver operating characteristics.

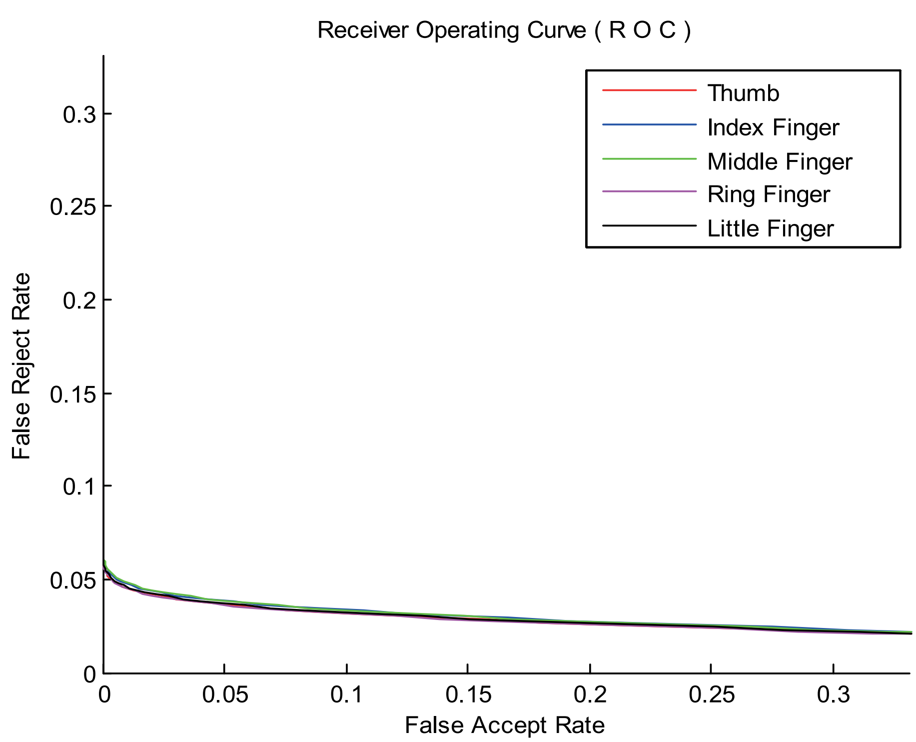

Fig. 17. Receiver operating characteristics for each finger.

Table 3. Finger wise EER computation.

Fingers	Thumb	Index Finger	Middle Finger	Ring Finger	Little Finger
EER	0.0375	0.0383	0.0415	0.0376	0.0392

Table 4. Comparison of proposed algorithm with existing methods available in literature.

Algorithms	# of people	Samples per person	Approach	Features	Performance	Recognition rate
Sanchez-Reilloet al. [44]	200	20	Various distances, GMMs, RBF	Hand/finger measurements	FAR=0.066 FRR =0.09	—
Woodard et al. [45]	42	2	Normalized correlation coefficient	Singe and Fused Fingers, linear regression technique	EER = 0.055	94
Fouquier [46]	750	6	Symmetric Kullback	Finger geometry measurement	EER = 0.0421	—
Proposed	100	4	HoG & k-NN	Geometrical features	FAR = 0.0309 FRR= 0.0312 EER = 0.0311	96.9

easily used for the tagging of fingers by using k-NN classifier, which classifies and identifies the fingers accurately. The experimental results show that these segmented images can be used effectively and efficiently for the development of the other stages of the fully automatic hand-based security system. Future work includes: 1) To carry out an advance research to increase the accuracy of the system; 2) Modification of pre-processing step so the significant characteristics of the image can be extracted; and 3) Investigation of methods that may reduce the computational cost of the system.

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