Graph Geometric Approach and Bow Region Based Finger Knuckle Biometric Identification System

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Abstract: Nowadays a biometric recognition system placed an important role in individual identification and authentication process. The user identities are authenticated by utilizing different biometric such as ear, face, eye, iris, palm, signature, finger knuckle and so on. From the various biometric features, finger-knuckle, having many advantages like the user acceptance of the outer-palm surface is very high, rich in texture feature, easily accessible, stable features because the features are never changed during the person emotionally and behavioral aspects. So, the proposed system uses the finger knuckle based biometric system for authenticating the user identities. Initially the captured biometric images are converted to the grayscale format and the noise has been removed by applying the Non-Local Median filter which improves the quality of the captured image. From the preprocessed image the contour has been extracted by using the Graph based Geometric Approach and the Principal Curvature based finger-knuckle-print Region has been located. The located key point is trained by Compositional Neural Networks and the matching is done with the help of the Levenshtein distance measure which determines whether an individual is authorized or not. Then the proposed system is implemented using PollyU finger knuckle database and the efficiency is analyzed in terms of false acceptance rate, false rejection rate and equal error rate.

Key words: Biometric recognition, grayscale image, non-local median filter, graph based geometric approach, principal curvature based region, levenshtein distance measure.

1. Introduction

The biometric is the method to authenticate the user identities using the human characteristics. The human characteristics are distinctive, measurable which may be physiological and behavioral characters [1]. There are several physiological characters like face, fingerprint, palm veins, face recognition, DNA, palm print, hand geometry, iris, retina features and the behavioral features like rhythm, gait and voice features which is used to ensure the authentication and access control [2]. These human traits based biometric system to enhance the security in various organizations, institutions, academic areas, bank transactions, attendance management and cloud computing applications. From the various human traits the finger knuckle biometric features are having the various benefits like, numerous image capturing, contact-less, user acceptance of the outer –palm surface is high, well defined texture feature, easily accessible and stable features because it does not change their characteristics during the personal emotions and behavioral aspects [3]. So, the finger knuckle print biometric feature provides higher security to user identities when compared to the other biometric features. Then the sample finger-knuckle print image is shown in the Fig. 1.

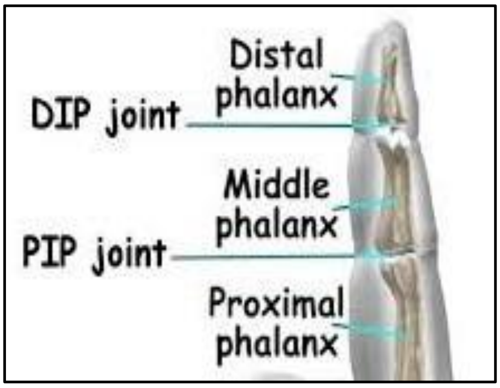


Fig. 1. Sample finger-knuckle print image.

Each finger-knuckle images has three joints namely, proximal phalanx, middle phalanx and distal phalanx. The first joint is where the finger joint the hand called proximal phalanx and second joint is called PIP or proximal interphalangeal joint. The last joint of the finger is called the distal interphalangeal joint, or DIP [4]. These finger –knuckle print joint features are used to ensure the security in the several authentication systems. Then the authentication is achieved by applying the image processing techniques and mining techniques. So, the proposed system uses the PollyU finger knuckle database images and the noise have been removed by applying non-local median filter [5]. Then the shape of the finger-knuckle image is segmented using the Graph based Geometric Approach and the Principal Curvature based finger-knuckle-print Region has been extracted [6]. The extracted features are trained and classified by utilizing the Compositional Neural Networks. Finally the template matching is done with the help of the Levenshtein distance measure and the performance of the system is evaluated using the different biometric features.

Then the remaining of this paper organized as follows, Section 2 summarizes the related works for biometric based person authentication, Section 3 deals with the detailed proposed methodology and Section 4 discusses the results and then the Section 5 describes the conclusion.

2. Related Works

Biometric process enhances the security in terms of identification and authentication using the finger-knuckle features. Kumar *et al.* [7] proposes an automatic finger-knuckle print identification system using the image preprocessing, enhancement, normalization and matching steps. The captured finger-knuckle images are processed and the finger surface joining distal phalanx and middle phalanx bones features are extracted which is classified during the authentication process. Then the performance of the proposed system is evaluated using the 503 finger- knuckle image which is captured from the 4-7 years subjects. This finger-knuckle biometric system used in the forensics and biometrics applications with effective manner. KamYuen Cheng *et al.* [8] develop an online based smart phone finger-knuckle biometric system for managing the privacy to the user identities. The captured images are preprocessed and the effective regions are segmented. The segmented image features are retrieved by applying the Gabor filter. Then the performance of the proposed system is evaluated using the 561 knuckle images, 187 finger images from the 109 users, which is implemented in the c and c++ programming languages. Finally the implemented smart phone based knuckle system ensures the security to the user identities.Michael et al., [9] author proposes a contactless palm print and knuckle print recognition system for authenticating the user details. Initially the knuckle prints are captured from the low resolution video stream and the knuckle features are extracted using the ridgelet transform. The extracted features trained and classified using the support vector machine also fuse the palm print and finger knuckle prints which is used to establish the biometric system in the real time applications.

Meraoumia *et al.* [10] improves the multimodal biometric system using the palm print and finger knuckle print biometric features. The captured features are processed by using the Phase-Correlation Function (PCF). Then the two biometric features are combined with the help of the matching score level and the performance of the system is evaluated using the recognition rate. Thus the proposed system achieves better results when compared to existing methods. Mahesh Kumaret al.,[11] proposes a finger print knuckle biometric system for improving the authentication and security to the user personal information's. The captured knuckle print biometric features are preprocessed and the local, global texture features are extracted by utilizing the symmetric discrete orthonormal Stockwell transform. The extracted local features further enhanced by Stockwell transform and the global features are enhanced using the Fourier Transform. After extracting the local and global features are compared using the weighted average difference metrics to ensure the matching similarity between the knuckle print features. Then the performance of the system is analyzed using the PolyUFKP database which achieves the minimum error rate and maximum recognition rate when compared to the other methods.

Vaibhav *et al.* [12] develops the novel biometric recognition system using the Radon Transform. The captured finger knuckle biometric image considered as the texture image which is preprocessed and the noise has been removed for improving the recognition rate. Then the different direction based features are extracted using the Random transform which is classified by applying the weighted average difference measures. Then the performance of the system is evaluated using the PolyUFKP database knuckle print images which is analyzed using the 60 different directions ranging from 0-180 degree with the interval of 3 degrees. Then the feature vectors are mapped according to the 256×60 size, which provides the 94.33% recognition rate. So, the proposed system uses the PolyURKP database images and which is processed by applying the contour extraction and feature location process by utilizing the Graph based Geometric Approach and the Principal Curvature. Then the located feature are matched with the help of the Levenshtein distance measure that ensures the efficient biometric authenticate system with minimum error rate.

3. Proposed Finger-Knuckle Print Biometric System

In the modern technology the user information and credential information's are critical issues. To overcome the critical issues the authentication and access control mechanism need to be improved which is done with the help of the biometric system. So, the paper proposes a finger-knuckle print based biometric system for managing the user identities because it does not change their character due to the emotional behaviors. In the proposed system PolyU Finger-knuckle database [13] is used to recognize the people's identities. It consist of the four different stages such as image color transformation, noise removal, feature extraction and matching which are used to authorize the user information or identities. The proposed system block diagram is shown in following Fig. 2.

The Fig. 1 depicted that the proposed finger-knuckle print biometric approach which has two stages namely, training and testing stages. In the training stage the finger-knuckle images are preprocessed by non-local median filter and the contour related regions are extracted. From the contour image the key point has been located which is trained by using the compositional neural networks which is stored as the template in the database which is used for further matching process. The next stage is testing process in which user finger-knuckle images is preprocessed and the features are extracted by using the same feature extraction method which was compared to the database template by using the Levenshtein distance measure. Based on the matching condition (threshold value) users are validated for accessing their information. The rest of the section describes the detailed proposed finger-knuckle print biometric methodology.

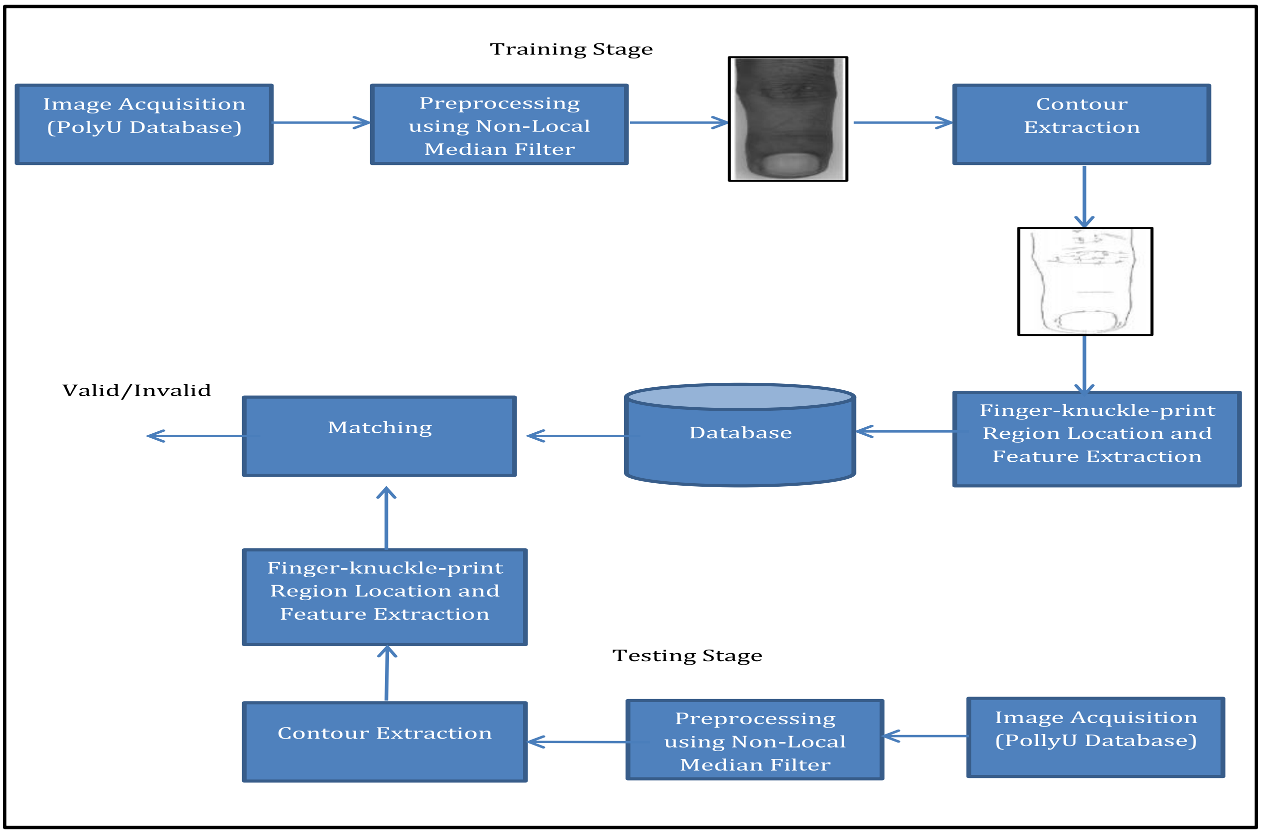


Fig. 2. Proposed finger-knuckle biometric system architecture.

3.1. Color Transformation

In the finger knuckle biometric approach, identities are managed by using the finger- knuckle image. Initially the finger-knuckle images are captured which may be in the color which is difficult to process because it consumes more time and difficult to extract the key point location. So, the RGB color images are transferred into the gray scale image [14] which performance better when compared to the color image. The gray scale image has three colors namely black, white and in between the gray color. In that combination, black pixel has (0,0,0) values, white pixel has (255,255,255) values and the gray pixel has (127, 127, 127)Medium values. Then the gray scale value is computed by using the weighted average of these above red, green and blue value. The gray scale weighted average GS is estimated by equation 1.

$$GS = 0.2989 * Intensity(r) + 0.58701 * Intensity\,(g) + 0.1140 * Intensity\,(b) \quad (1)$$

The above equation 1 helps during the color image transformation. In this paper finger-knuckle image are taken from the PolyU Database which contains a list of gray scale images so, there is no needed for transformation during the processing. If the images are taken from the camera, then the above color transformation should be required.

3.2. Noise Removal using Non Local-Median Filter

The first step of preprocessing is noise removal which is done with the help of the Non-Local Median Filter (NLMF) [15]. The NLMF filter removes the noise present in the finger-knuckle image by utilizing the large amount of the self-similarity concepts. In the image the pixel values are measured in terms of the intensity of light that can be represented as follows,

$$v(i) = u(i) + n(i) \tag{2}$$

where $v(i)$ is defined as the observed value from the given image, $u(i)$ is defined as the "true" value and $n(i)$ is defined as the noise agitation at a pixel$i$.

The main aim of the image de-noising approach is to obtain the noiseless clear image from a noisy measurement. The influence of noise on a digital image can be better modeled by the addition of a Gaussian white noise. Based on this assumption, $n(i)$ are independent, identically-distributed Gaussian values with variance $\sigma^2$and zero mean. In the image, considered the pixel at p, Similar pixel neighborhoods give a great weight, $w(p, q1)$ and $w(p, q2)$, while much unlike neighborhoods give a lesser weight such as $w(p, q3)$. Each pixel p of the NLM filtered image is calculated by using following equation

$$NL(V)(p) = \sum_{q\varepsilon V} w(p,q)V(q) \tag{3}$$

where V is defined as the noisy image, and weights $w(p,q)$ meet the subsequent conditions $0 \leq w(p,q) \leq 1$ and $\sum_q w(p,q) = 1$.

Each pixel is known as the weighted average of whole image pixels. The weights depend on the similarity between the neighborhoods of pixels p and q [1, 2]. So as to calculate the similarity, initially define the proper neighborhood. Assume N_i be the center of the square neighborhood on pixel i with a user-defined Radius Similarity(R_{sim}). To find the two neighborhood similarity is done by considere the weighted sum of squares is as follows

$$d(p,q) = \|V(N^p) - V(N^q)\|^2_{2,F}[1,2] \tag{4}$$

where F is defined as the neighbourhood filter employed to the neighborhood's squared difference. The weights is defined as follows

$$w(p,q) = \frac{1}{Z(p)} e^{\frac{-\max(d^2 - 2\sigma^2(p,q)}{h}} \tag{5}$$

where σ is as defined as the standard deviation of the noise and $2\sigma^2$ are set to 1. Where $Z(p)$ is defined as the normalizing constant is defined as follows

$$Z(p) = \sum_q e^{\frac{-d(p,q)}{h}}[1,2] \tag{6}$$

where h is defined as the weight-decay control parameter. As earlier mentioned, F is known as the neighborhood filter with R_{sim}. The weights of F are computed is as follows

$$F = \frac{1}{R_{sim}} \sum_{i=m}^{R_{sim}} 1/(2 \neq i|1)^2 \tag{7}$$

where m is defined as the distance the weight is from the neighborhood filter's center. The F provides higher weight to pixels near the neighborhood center, and provide lower weight to pixels near the neighborhood edge. Finally, these are averaged at each pixel location to generate the final de-noised image which is shown in the Fig. 3.

3.3. Finger-Knuckle Contour Extraction

The next phase is finger-knuckle contour extraction in which the outer edges are segmented from the preprocessed image with effective manner. The preprocessed image has two pixel values namely background pixel (0) and the object pixel (1) which is used to extract the contour from the preprocessed image. The contour extraction consists of three stages like, point extraction, graph construction and point linking [16]. The first step is point extraction in which each pixel present in the image is extracted. The object consists of only two pixel values such as the pixel belongs to the foreground value and the pixel belongs to the object detection. From the extracted pixel value the contour of the image is constructed with efficient manner. Let the image I={F,B} where F={f_1,f_2,f_3… f_n}represents that the set of foreground pixel value and the B={b_1,b_2,b_3,…b_k} represents that the set of background pixel value. For every pixel present in the image I, the graph based method add the point p_i=(x_i,y_i) where p_i= fi, 0<i<n+1. These added point pixels are used to construct the graph for identifying the contour in the image. So, the geometric graph G=(V,E) has been constructed from the point P where V represents that the set of all the points in P and E denotes that the set of edges in the (p_i,p_j). Then the constructed geometric graph has particular threshold value like d(p_i,p_j) which is used to eliminates the hassles in the constructed graph. After eliminating the hassles points in the graph, the edges, center value has been calculated based on the graph radius. From the values the graph is constructed with efficient manner. Then the constructed graph points [17] need to be linked one to one for identifying the enhanced finger knuckle images. The point linking has been done with the help of the estimating the number of vertex in the all the direction. Initially the origin of the pixel (0,0) is identified and the which is always lies in the top left of the image and the Left_Most_Valid_Vetex() function is applied to the constructed graph for calculating the number of left most edges in the image. The calculated left vertex has at least x values and the degree value is greater than 1. During the vertex estimation process, if it has two top most value then select the y value as the number of vertex. Based on the calculation the number of vertex and degree value is calculated with clock wise direction. The estimated values are used to form the efficient knuckle print contour image and the Contour extraction algorithm is discussed as follows,

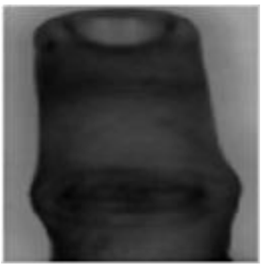
(a) . (b)

Fig. 3. a) Original Noise FKP Image, b) NLM based Noise Removed FKP Image.

Algorithm for Contour Extraction

Step 1: Extract contour (Geometric Graph G)
Step 2: V1=Left_Most_Valid_Vertex()
Step 3: V2=Find_Second_Valid_Candidate(v1)
Step 4: Edge=(v1,v2),s1=v1,s2=v2, C={v1,v2}
While s2 ≠v1 do
Step 5: Vq=Find_Valid_Candidate(s1,s2)
Step 6: S1=s2,s2=vq
Step 7: C=C∪ $(s1, s2)$
End while
ReturnC
end

Based on the above methods the figure knuckle print image edges are segmented with efficient manner and the sample image is shown in the Fig. 4.

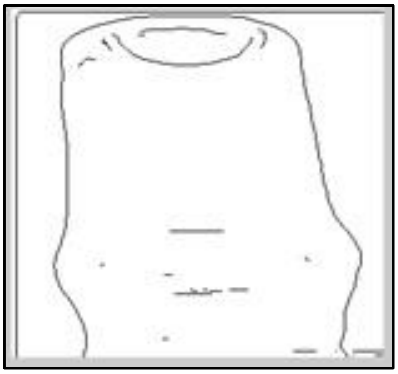


Fig. 4. Sample contour extracted finger knuckle image.

From the extracted contour finger knuckle image, the Principal Curvature based key point has been located which is explained as follows.

Finger-Knuckle Print Key point Location

The next step is finger-knuckle key point location which is done with help of the principal curvature based detector [18]. This method analysis, the keypoints in two ways like intensity based detectors and structure based detectors which detects the key points with different geometrical locations and structural features. Initially the principal curvature region has been estimated for detecting the key point present in the finger-knuckle image. The principal curvature region is calculated by applying the Hessian Matrix, which is defined as follows,

$$H(x) = \begin{bmatrix} L_{xx}(x) & L_{xy}(x) \\ L_{xy}(x) & L_{yy}(x) \end{bmatrix} \quad (8)$$

where $L_{xx}(x)$ is the second partial derivative of the image at a point x in the x direction and $L_{xy}(x)$ is the mixed partial second derivative of the image at a point x in the x and y directions. From the maximum and minimum eigenvalues of this matrix form two images that correspond to the white lines on black background and black lines on white background. Then the estimated principal curvature regions has been further enhanced by applying the watershed region algorithm. The watershed algorithm enhances the region by choosing the local minima of the gradient image value as the marker and marker position is used to determine the region automatically. From the detected principal curvature region the key point has been located using the scale invariance method. The scale invariance [19] method detects the local features from the contour image based on the relative positions. So, the method derives the key point with different direction, rotation, position of the input contour image. Initially the candidate key point has been detected by combining to work with the Gaussian Filter. So, maximum and minimum value have been calculated from the edge segmented image which is obtained as follows,

$$D(x, y, \sigma) = L(x, y, K_i\sigma) - L(x, y, K_j\sigma) \quad (9)$$

where $D(x, y, \sigma)$the difference of the Gaussian image is, $L(x, y, K\sigma)$ is the convolution value of the image, $I(x, y)$ is the Gaussian blur value,

$$L(x, y, K\sigma) = G(x, y, k\sigma) * I(x, y) \quad (10)$$

After detecting the key point, then the key point have been located for identifying the exact features of the image. The key point position has to be determined and the location, scale of the key point has been calculated by applying the Taylor series which is obtained as follows,

$$D(x) = D + \frac{\partial D^T}{\partial x} x + \frac{1}{2} x^T \frac{\partial^2 D}{\partial x^2} x \quad (11)$$

Then the orientation has been assigned as follows, which is used to identify the direction of the particular key point is measured by the magnitude and orientation estimation.

$$m(x, y) = \sqrt{\big(L(x+1, y) - L(x-1, y)\big)^2 + \big(L(x, y+1) - L(x, y-1)\big)^2} \quad (12)$$

$$\theta(x, y) = atan2\big(L(x, y+1) - L(x, y-1)\big), \big(L(x+1, y) - L(x-1, y)\big) \quad (13)$$

where, $m(x, y) = magnitude\ of\ the\ key\ image, \theta(x, y) = orientation\ \ the\ key\ point\ image$

Finally the key point has been located and detected from the scale invariance image region which is compared with the particular threshold value. If the calculated feature vale is within the threshold value which is considered as the finger-knuckle print features which is used to establish the authentication process.

3.4. Template Matching

The last step is template matching which means the user query related features are compared with the database features to authenticate and manage the user identities. In this paper the template matching is performed with the help of the Compositional Neural Networks based training and the Levenshtein distance measures which is explained as follows

3.4.1. Feature training using compositional neural networks

The above extracted features are trained by using the Compositional Neural Networks [20] which is one of the supervised learning methods. The neural network has three layers, namely input layer, hidden layer and output layer. The input layer receives the extracted features as input, each layer has weight and bias value for reducing the error while train the neural network. The hidden layer receives the input from the input layer and transform into the output form which is done as follows,

$$Net\ output = \sum_{i=1}^{N} x_i * w_i + b \quad (14)$$

During the net output calculation the neural network is trained by using the particular learning and activation function which updates the weights and bias as defined as,

$$X_{k+1} = X_k - [J^T J + \mu I]^{-1} J^T e \quad (15)$$

The CPPN's network applied the combination of activation functions like sigmoid and Gaussian function to whole the input space for optimizing the bias value while calculating the net output. This choice of the functions for the canonical set can be towards the specific types of patterns. Based on the knuckle print features symmetric function like Gaussian produce symmetric pattern and fracke like patterns are extracted which is stored as the template in the database. Then the sample finger-knuckle print image template is shown in the Fig. 5.

Fig. 5. Sample stored template.

These stored templates are used to matching process which is described as follows,

3.4.2. Feature matching using levenshtein distance

The final step is template matching which means, user query related features are compared with the database features to manage the people's identities. In this paper, the similarity matching [26] process is done with the help of Levenshtein Distance (LD) measure [21]. The LD method identifies the difference between training and testing features with the threshold value. So, in the proposed system user features (Query template) compared with the training feature set by using the following equation 16.

$$\mathrm{D_{a,b}} = \begin{cases} \max(\mathrm{i,j}) & \text{if } \min(\mathrm{i,j}) = 0, \\ \min \begin{cases} \mathrm{D_{a,b}}(\mathrm{i}-1,\mathrm{j}) + 1 \\ \mathrm{D_{a,b}}(\mathrm{i},\mathrm{j}-1) + 1 \\ \mathrm{D_{a,b}}(\mathrm{i}-1,\mathrm{j}-1) + 1_{(\mathrm{a_i} \neq \mathrm{b_j})} \end{cases} & \text{otherwise} \end{cases} \tag{16}$$

where

$D_{a,b}$ is the distance between the user query and template features,

$1_{(a_i \neq b_j)}$ is the indicator function which is equal to 0 when $a_i = b_j$

The length of the features like template and user query with respect to the i and j which is used to estimate the distance between the features. Then the computed similarity value is compared with the threshold value 0.3. If the value is greater than the threshold value, then the user related query value is considered as the valid template otherwise leaves as the invalid one. Thus the proposed system extracts the principal curvature based features of the finger knuckle print and those features are trained by Compositional Neural Networks, matching is done with the help of the Levenshtein Distance measure.

4. Result and Discussion

Thus the proposed biometric system used to establish the authentication and authorization to the user identities with the help of the finger knuckle print biometric features because it has stability features which means it never changes their characteristics based on the personal emotions. In the proposed system the PolyU finger knuckle print image database used for recognizing the user identities. Then the sample finger knuckle images are shown in the figure 6 which was taken from the PolyU FKP database [22].

Fig. 6. Sample PolyU knuckle print images.

The Above Included Finger Knuckle Print Images Are Taken From The PolyU Database Which Has Collected From Both The Male And Female Volunteers. During the year 2006-2013 the knuckle images are acquired using contactless hand held camera in the Hong Kong Polytechnic University campus and IIT Delhi Campus. The database consists of 2515 finger dorsam images from the middle finger of 503 subjects, all the images are in bitmap (*.bmp) format. The captured images are converted to the gray scale images and the key point has been located using the principal curvature method and matching is done with the help of the Levenshtein Distance measure. Then the performance of the proposed system is evaluated using the False Acceptance Rate (FAR), False Rejection Rate (FRR) and Equal Error Rate (ERR).

4.1. False Acceptance Rate

False Acceptance Rate (FAR) [23] is the process of identifying that rate of unauthorized user acceptance during the identity identification process. The FAR is measured by using the following equation 17.

$$FAR = \frac{Number\ of\ features\ accepted}{Number\ of\ features\ tested} \times 100 \tag{17}$$

From the equation 17 False Acceptance Rate of different biometric features such as fingerprint, face, nail and finger knuckle print was obtained using the different matching algorithm and their related graph is shown in the following Fig. 7.

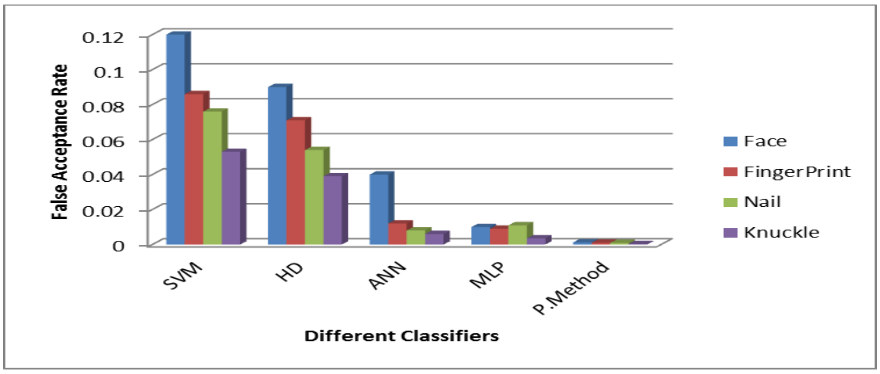


Fig. 7. False acceptance rate.

From the above Fig. 7 it is clearly shown that the knuckle print based biometric features are provided best result because the other biometric features are having a low false acceptance rate when compared to the knuckle biometric features while using the different matching algorithm like SVM [24], Hadoruff distance measure (HD)[25], Artificial Neural Networks (ANN)[26], Multilayer Perceptron(MLP) [27].

4.2. False Rejection Rate

False Rejection Rate [28] is the process of incorrectly rejecting the authorized user during the matching process which was measured in terms of percentage. The FRR is measured by using the following equation 18

$$FRR = \frac{Number\ of\ \ original\ features\ rejected}{Number\ of\ original\ features\ tested} \times 100 \tag{18}$$

From the equation 18 False Rejection Rate of different biometric features such as fingerprint, face, nail and knuckle print related FRR is representation is shown in the Fig. 8.

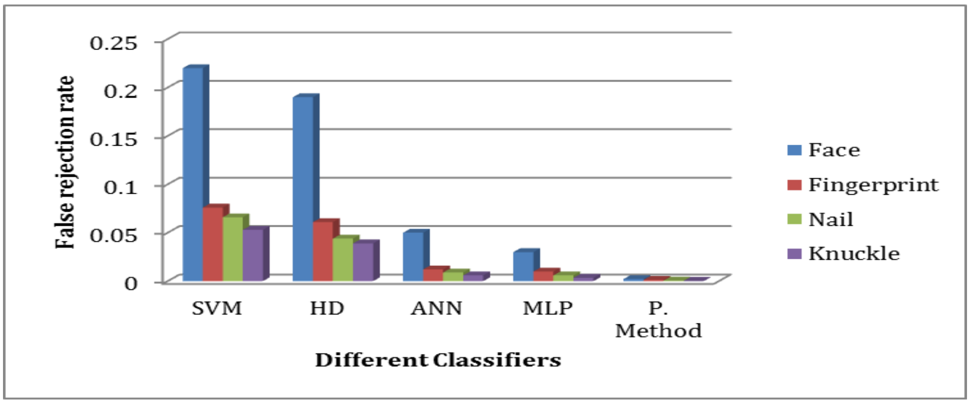


Fig. 8. False rejection rate.

From the above figure 8 it is clearly shown that the knuckle based biometric features are provided best result because the other biometric features are having a high false rejection rate when compared to the knuckle print biometric features while applying the different classifiers.

4.3. Equal Error Rate

Equal Error Rate [29] is the rate in which acceptance and rejections are equal which is easily calculated from the above described FAR and FRR values. Then the Equal Error Rate value is shown in the following figure 9 in which the knuckle biometric features are having the lower rate value.

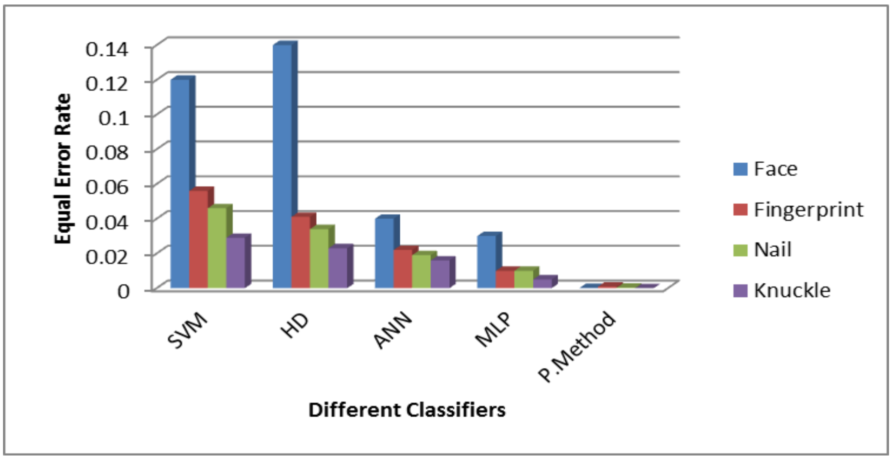


Fig. 9. Equal error rate.

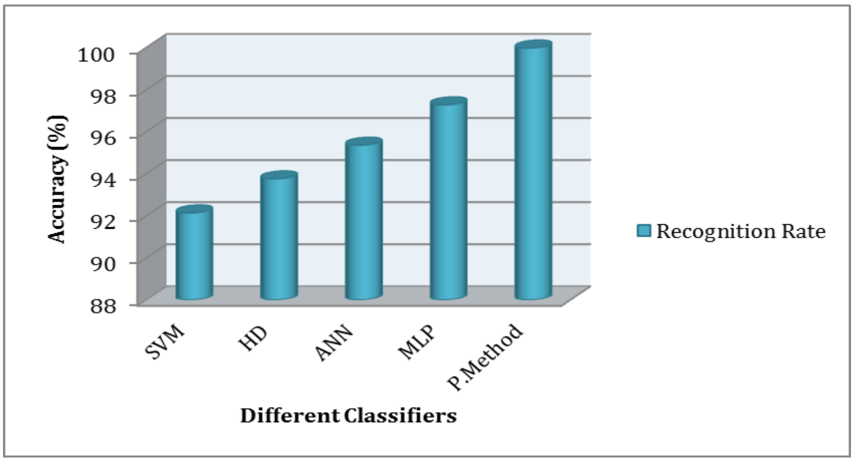


Fig. 10. Accuracy.

From the above discussions the proposed system and the knuckle print biometric features consumes minimum error rate and high false rejection rate when compared to the other methods. These minimum error rate increases the recognition rate which is shown in the following Fig. 10.

From the above figure 10 depicted that the proposed method achieves the higher recognition rate when compared to other existing classifier methods. These discussed performance metrics are used to justify the knuckle biometric features are best to identify and classify the person from the unauthorized activities.

5. Conclusion

Thus the paper authenticates the user identities and personal information using the principle curvature descriptors and the Levenshtein distance measure. In this paper the PolyU finger knuckle image database is used to analyze the user identities which were captured from the year 2006-2013 from the IIT Delhi university campus. The captured images are converted to the gray scale images for improving the system performance during the further recognition process. Then the noise presented in the images is removed in terms of pixel by pixel and the contour has been extracted by forming the geometric constructed graph. From the graph the key point is located using the principal curvature regions with different direction and rotation of the image contour. Then the extracted features are trained with combination of the training and activation function and the matching is done with the help of the Levenshtein distance measure which validates the user query template. Thus the performance is evaluated with the help of False Acceptance Rate, False Rejection Rate, Equal Error rate and Recognition Rate.

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