Fusion of Palmprint and Finger-Knuckle-Print for Human Personal Recognition

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***Abstract*—This paper proposes a multimodal human personal recognition system based on palmprint and knuckleprint. Palm is the inner surface of the hand that extends from the wrist to the base of the fingers and contains a lot of unique pattern of ridges, valleys, principal lines and wrinkles. On the other hand, knuckle is at the outer part of a finger at its joint. Pattern formation at finger knuckle are unique and hence provide good discriminative power. In this work edge based local binary pattern (ELBP) is used for image enhancement. Corner features are tracked using LK-tracking constrained by Gaussian response code and some geometrical constrains. This system has been tested on some publicly available databases such as CASIA-PALM, PolyU-PALM and PolyU-KNUCKLE. The system has been found to perform well over these databases along with self created chimeric multimodal databases. The fusion has shown significant improvements.**

Keywords*—*Biometrics, Multimodal, Gaussian Code, LK-Tracking, Corner features

I. INTRODUCTION

Today security is one of the major issues in the high tech world. Most of the large scale organizations are in need of secure system which can be used for human identification. Token based and knowledge based systems are traditional ways for human identification but they are more vulnerable to security threats. A token based identification system uses a token to get access into the system. Birth certificate, voter id card, PAN card etc. are some commonly used tokens. Knowledge based identification systems associate a human being with some kind of personal information such as password. The subject is asked to reproduce this knowledge correctly to clear the security check.

A biometric based security system makes the decision on the identity which is based on individual's unique physical or behavioral characteristics. Fingerprints, iris, face, ear, hand or palm, are some of the well known physiological biometric traits where as behavioral characteristics include voice, handwriting or typing rhythm. They are easier to use and harder to circumvent. Personal traits cannot be lost or forget as compared to keys and passwords. They are also be very difficult to copy. For this reason biometric security systems are considered to be safer and more secure than traditional security systems. But each trait has its own pros and cons and no single biometric efficiently fulfills the requirements of all the applications. The limitation due to single biometric trait can be over come by using multiple traits.

A major problem with any biometric system is, that recognition rate starts to drop as the number of subjects in the database increases. Multimodal biometric systems can improve the result over large database as compared to unimodal biometric systems. It can also overcome the issue of non universality, since use of multiple biometric characteristics can cover large population. They have shown higher robustness to circumvention as it is difficult for an adversary to create physical artifact of multiple biometric traits. Both palm and knuckle are not affected by pose or emotions and are least affected by aging and remains stable over a long period of time. They are rich in texture pattern and hence can be more discriminative and unique.

In this work a bi-modal personal authentication system is proposed using palm and knuckleprint. Edge based local binary pattern (ELBP) has been used for image enhancement and corner features are tracked using LK-tracking constrained by Gaussian response code and some geometrical constrains. This system has been tested on some publicly available databases such as CASIA-PALM, PolyU-PALM and PolyU-KNUCKLE.

II. LITERATURE REVIEW

In this section a detailed literature review for palmprint, knuckleprint and multimodal based personal recognition system is presented.

Palmprint : The process of acquiring palmprint images is based on either ink marking or digital imaging. To facilitate ROI extraction, images are acquired under constrained environment. Acceptability of systems using ink marking technique is low since it needs high user cooperation. System described in [1] makes use of CCD to acquire palm image where pegs are used to control hand alignment. In [2] a digital scanner with pin markers are used for image acquisition. In [3–5] hand image acquisition is done without any constraints. In such systems, extraction of ROI is a challenging issue. ROI extraction should be carefully designed to address problems of rotation and translation. Systems described in [3, 6, 7] makes use of valley points near ring and middle fingers to find ROI.

The verification system proposed in [8] makes use of prominent palm lines for feature extraction. Orientation of these lines and a set of points along these lines are extracted as

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features. Point matching technique is employed to match features of query and enrolled images. This matching technique addresses the issue of non-rigid distortion as well as problem of outlier points present in both query and enrolled images. In [9] an online personal identification system using palmprint has been proposed. Gabor filter of particular orientation is applied to palmprint images to obtain the Gabor phase, which is binarised using zero crossing to form the feature vector. Matching between query and enrolled palmprint is done using normalized hamming distance. In [10] Competitive Coding Scheme is used for feature extraction from palm print images. Orientation information is extracted from palm lines using multiple 2-D Gabor filters. This information is used to create the feature vector called Competitive Code. Comparison of two such codes is done with the help of angular matching. The scheme in [10] is based on feature-level fusion. To extract the phase information, various Gabor filters with different orientations are used. These phase information are then merged according to a fusion rule to produce a feature called the FusionCode. Comparison of two such FusionCodes is done using normalized hamming distance. The recognition systems proposed in [11] is based on minutiae and ridges. A minutiae code is formed based on minutia information such as minutia type, ridge count and number of minutia present in the neighborhood.

In [12] a palmprint based recognition system which is based on Discrete Cosine Transform(DCT) has been proposed. Matching makes use of Canberra distance to match query image with the enrolled image. In [13] a palmprint based recognition system which is based on eigenspace has been proposed. The verification system proposed in [14] is based on Scale Invariant Feature Transform (SIFT). Use of SIFT for feature extraction makes the system invariant to scale. Feature vector from two palmprint images can be considered as "matched", if Euclidean distance between them is less than a threshold.

Knuckleprint : In [15], personal authentication system based on 2D finger knuckle surface has been proposed. An acquisition system has been presented to capture outer hand images from which ROI is extracted. Feature extraction and matching are based on subspace analysis methods such Principal component analysis (PCA), Linear discriminant analysis (LDA) and Independent Component Analysis (ICA). The system proposed in [16] makes use of multiple gabor filters for feature extraction. The Gabor filter outputs three types of information (i) magnitude (ii) phase (iii) orientation. A method is proposed which combines magnitude with orientation for feature extraction and matching. The verification system proposed in [17] is based on Band-Limited Phase-Only Correlation (BLPOC). An algorithm is proposed to extract ROI using convex direction coding. Also a BLPOC based method is proposed to register a knuckleprint image and further to calculate the matching score.

The recognition system proposed in [18] is based on gabor filter and local binary pattern (LBP), which has good gray-scale and rotation invariance. It can also tackle uneven illumination problem. It uses 8 gabor filters and each of these gabor feature representation of images are divided into blocks. Later LBP histogram are computed and matched using Chi square distance.

Quality estimation of any biometric trait is also very important and a difficult task. Good amount of work has been done to estimate the quality of face and fingerprint images due to the presence of some very specific texture. But limited work is done so far for iris [19], knuckleprint [20] and palmprint quality estimation as its lacks any such specific texture and structure. Some more work on knuckleprint and palmprint recognition is reported in [21–23] using SIFT and SURF fusion and $LK-$tracking of corner features.

Multimodal : In [24] trimodal hand based biometric system has been proposed that fuses finger geometry features with knuckleprint and palmprint features. Length, mean, width like features has been used for finger geometric while gradient and corner based features got utilized for knuckle and palmprint respectively. Later hierarchical hand metric matching is done over their indigenous database. In [25] contact-less palmprint and knuckleprint acquisition and fusion has been proposed using directional coding and Ridgelet transformation respectively. In [26] fusion of palm and knuckleprint has been done using Hidden Markov Model (HMM). Recent some multimodal systems has been reported in [27–29] fusing various combinations of palmprint, knuckleprint and iris images.

III. Background Work

This section deals with the background materials needed to design the proposed biometric recognition system. It describes the techniques used for feature extraction. Corner points are considered as features for the proposed system. It also discusses Lukas-Kanade Tracking algorithm [30] to track corner features.

A. Good Corner Features

Performance of a biometric system highly depends of the choice of the features considered for a specific trait. For a particular feature point in enrolled image, the probability by which it can be tracked in the corresponding query image is "high", if the feature point possesses some unique or nearly unique property. A point is said to be a corner if it is associated with strong derivatives in two orthogonal directions. Autocorrelation matrix $(M(x,y))$ which can be is used to classify a point as a corner feature point can be defined as follows:

$$M(x,y) = \begin{pmatrix} \sum_{-K\le(i,j)\le K} w_{ij} I_x^2(x+i,y+j) & \sum_{-K\le(i,j)\le K} w_{ij} I_x(x+i,y+j) I_y(x+i,y+j) \\ \sum_{-K\le(i,j)\le K} w_{ij} I_x(x+i,y+j) I_y(x+i,y+j) & \sum_{-K\le(i,j)\le K} w_{ij} I_y^2(x+i,y+j) \end{pmatrix} \quad (1)$$

where, $I_x(x,y)$ and $I_y(x,y)$ are derivatives in x-direction and y-direction respectively that are calculated using sobel operation, w_{ij} is the weight assigned to the neighborhood points of the pixel (say (x, y)) in consideration. The matrix M can have two eigenvalues and those points where auto-correlation matrix of second derivative yields two large eigenvalues are said to be corners. According to Shi and Tomasi [31] when both the eigenvalues are greater than the threshold then that point is said to be a Good Corner Point.

B. Lukas Kanade Tracking

Lukas Kanade Tracking algorithm is used to track points in between two frames. For a feature at time t located at (x, y) in first frame which has moved to location (x_1, y_1) in next δt time interval where,

$$x_1 = x + \delta x$$

$$y_1 = y + \delta y$$

The value of $I(x, y, t)$ can be considered as the intensity of pixel (x, y) at time t. To track point (x, y) of first frame in the second frame, LK Tracking relies on following three properties.

1) **Brightness Consistency :** The pixel under consideration should not change its visual characteristics much as it moves from the first frame to the second frame. For example, when working with gray images there should not be significant variation in brightness of the pixel.
2) **Temporal Persistence :** Displacement of pixel from its location in the first frame to the second frame must be small. Approximate value of $I(x+\delta x, y+\delta y, t+\delta t)$ can be calculated as follows (using Taylor series) :

$$\frac{\delta I}{\delta x}\delta x + \frac{\delta I}{\delta y}\delta y + \frac{\delta I}{\delta t}\delta t = 0 \qquad (2)$$

Dividing both sides of above Equation by δt one can get

$$I_x V_x + I_y V_y = -I_t \qquad (3)$$

where, V_x is the component for optical flow velocity in x-direction, V_y is the component for optical flow velocity in y-direction, I_x is derivative of $I(x, y, t)$ with respect to x, I_y is derivative of $I(x, y, t)$ with respect to y, I_t is derivative of $I(x, y, t)$ with respect to t.
3) **Spatial Coherence:** LK tracking assumes a square window of 5×5 in which all pixel have coherent movement. Substituting values for each of these 25 pixels $(P_1, P_2 ... P_{25})$ in the Equation 3, one can have a linear system of 25 equations which can be solved by least square method as follows :

$$C \times V = D;\ with\ C = \begin{pmatrix} I_x(P_1) & I_y(P1) \\ \vdots & \vdots \\ I_x(P_{25}) & I_y(P_{25}) \end{pmatrix} \qquad (4)$$

here,

$$V = \begin{pmatrix} V_x \\ V_y \end{pmatrix} \quad [\ Velocity\ Vector\ ]$$

Fig. 1: Regions used to compute Gaussian Response Code

$$D = \begin{pmatrix} I_t(P_1) \\ \vdots \\ I_t(P_{25}) \end{pmatrix} \quad [\ Temporal\ Derivatives\ ]$$

Derivatives of image I in x, y directions of i^{th} neighboring pixel $i \in (1..25)$ are represented by i^{th} row in C. Temporal derivative of image of i^{th} neighboring pixel is represented by the i^{th} row in D. Estimated flow vector $(V^{'})$ of the feature point in consideration can be determined as :

$$V^{'} = (C^T C^{-1}) C^T (-D) \qquad (5)$$

The Position vector $F^{'}$ of any feature point in the second frame can be calculated from its initial position vector $I^{'}$ and estimated flow vector $V^{'}$ as :

$$F^{'} = I^{'} + V^{'} \qquad (6)$$

C. Gaussian Response Code

Gaussian Response Code (GRC) performs encoding based on the relationship between two image regions. A typical two-dimensional Gaussian function is defined as :

$$G(x, y) = Ae^{-(\frac{x-x_0{}^2}{2\sigma_x^2} + \frac{y-y_0{}^2}{2\sigma_y^2})} \qquad (7)$$

Gaussian response $(GR(x, y))$ for any pixel (x, y) based on Equation 7 can be calculated as:

$$GR(x, y) = \sum_{0 \le (i,j) \le 5} I(x+i, y+j) \times G(i, j) \qquad (8)$$

The Gaussian Response Code for two regions as shown in Figure 1 can be computed as :

$$GRC = \begin{cases} 1 & \textbf{if}(GR(x, y) - GR(x_1, y_1)) \ge 0 \\ 0 & \textbf{if}(GR(x, y) - GR(x_1, y_1)) < 0 \end{cases} \qquad (9)$$

Hence, Gaussian response code for a pixel is a 8-bit vector whose i^{th} bit represents Gaussian Response Code of its surrounding patch with i^{th} neighborhood patch as eight neighboring patches are considered.

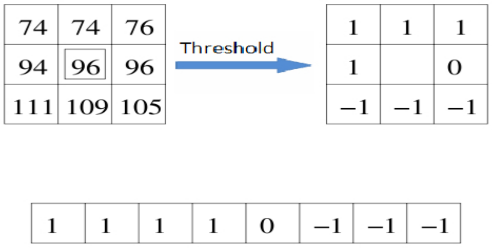


Fig. 2: The basic LBP Operator

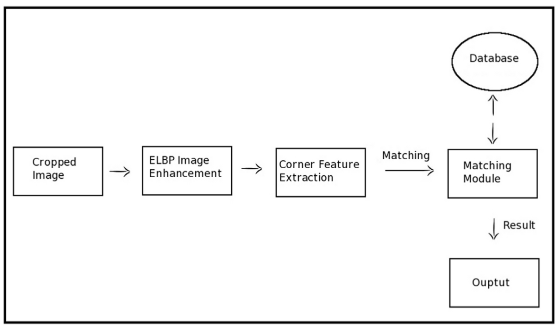


Fig. 3: Schematic Diagram of Proposed System

D. Local Binary pattern

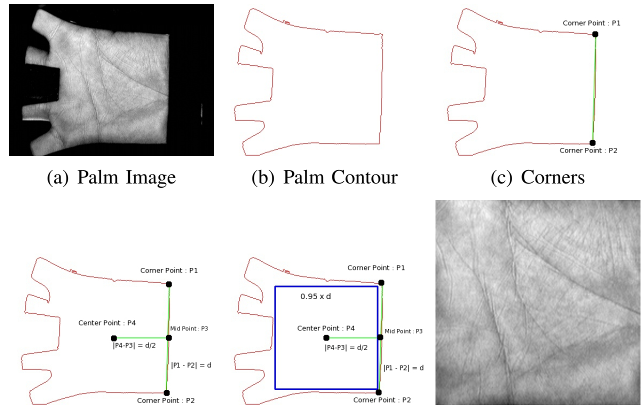
Local Binary Pattern (LBP) performs encoding of a pixel by performing thresholding of the neighborhood pixel's, relative gray value into a binary pattern. The LBP code is invariant to some amount of rotation and illumination. Figure 2 shows an example of LBP vector corresponding to its 8-neighborhood. Thresholding any neighborhoods pixel p with respect to the central pixel c can be done as follows :

$$LBP(c,p) = \begin{cases} 1 & \textbf{if}(I(c) \geq I(p)) \\ 0 & otherwise \end{cases}$$

where, $I(c)$ and $I(p)$ are gray values of central pixel c and neighborhood pixel p respectively.

IV. Proposed Approach

This section presents a biometric system which uses palm and knuckleprint images for personal authentication. It consist of four major components : ROI extraction, Image enhancement, Feature extraction and Matching. A schematic diagram of the proposed system is shown in Figure 3. The cropped image acts as an input to pre-processing module where edge based local binary pattern is used to enhance palm and knuckle images. From this enhanced image, the corner points are extracted. The matching module uses LK tracking algorithm to track these corner features and comes up with an appropriate decision.



(a) Palm Image (b) Palm Contour (c) Corners (d) Center (e) Bounding Box (f) ROI

Fig. 4: ROI Extraction Steps

V. ROI Extraction

This section discusses the process of ROI extraction from the palmprint of the hand image. ROI is the square area within the palm image. Form each hand image, a contour (C) is extracted which gives the boundary of the hand as shown in Figure 4(b). Contour C is traversed to get two corner points (P_1, P_2) located at the base of hand. Let point P_3 be the mid point of P_1 and P_2 as shown in Figure 4(d). Center point P_4 is calculated such that $\|P_3$ - $P_4\|$ = $(\|P_1$ - $P_2\|)/2$. With P_4 as center, a square box, as shown in Figure 4(e), is extracted from the hand image to extract the required palmprint ROI as shown in Figure 4(f). Side length of this square has been experimentally calculated and is set to $0.95 \times (\|P_1$ - $P_2\|)$. Steps for extraction of ROI is given in Algorithm 4.1. The knuckleprint images are supplied as already cropped.

Algorithm 4.1: $ExtractROI(I)$
Input: I: Hand Image
Output: ROI: Region of interest of hand image I
Extract contour C of the hand image I.
Traverse contour C to get corner points (P_1, P_2).
d = $\|P_1$ - $P_2\|$.
P_3 = Mid point of P_1, P_2.
Find point P_4 such that line (P_1, P_2) is perpendicular to line (P_3, P_4) and $\|P_3$ - $P_4\|$ = $d/2$.
Square box(Figure 4(e)) centered at P_4 with length of side as $0.95 \times d$ is the required ROI.
return ROI

VI. Image Enhancement

Knuckleprint and palmprint images are rich in edges which possess characteristics that are distinct across individuals. Every pixel in the image is encoded using Edge Based Local Binary Pattern (ELBP)to enhance the image. These enhanced images are robust to illumination. Some enhanced knuckleprint and palmprint images are shown in Figure 5. Edge detection is done to pre-process the image using Sobel edge operator. Vertical edge map is obtained when sobel operation is applied in horizontal direction. For every pixel $P(x, y)$ in this vertical edge map, ELBP (8-bit binary vector) is calculated. The j^{th} bit of this vector is calculated as follows:

$$ELBP_j = \begin{cases} 0 & Neighbor[j] < threshold \\ 1 & otherwise \end{cases}$$

where $Neighbor[j]$ represents horizontal gradient of the j^{th} neighbor of the pixel $P(x,y)$ and $j \in (1, 2...8)$. Pixel (x, y) in enhanced image represents the ELBP value of the corresponding pixel in the vertical edge map. It can be observed that any change in the image because of variation in the illumination condition causes changes in the gray scale values but ELBP value remains stable because the strong edge pattern near the pixel remains to be more or less same. The Algorithm 4.2 can be used to enhance any sample.

Algorithm 4.2: $ELBPEnhancement(Q)$
Input: Q: Query Image
Output: E: Enhanced Query Image
Apply sobel operator on Q to get a gradient image T.
h, w = height and width of T
for $i \leftarrow 0$ **to** $(h-1)$ **do**
    for $j \leftarrow 0$ **to** $(w-1)$ **do**
        sum=0
        exp=0
        for $k \leftarrow -1$ **to** 1 **do**
            for $l \leftarrow -1$ **to** 1 **do**
                if $(k! = 0 \parallel l! = 0)$ **then**
                    sum = sum + $(2^{exp}) * (T(i,j) > T(i+k, j+l))$;
                    exp=exp+1;
            E(i,j) = sum
return E

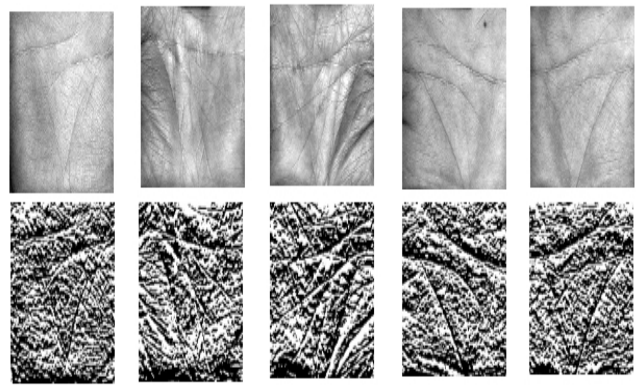
VII. Feature Extraction

Good Corner points are extracted as features from the enhanced image. As discussed in [31], good corner points are associated with orthogonal derivatives and hence are more likely to be unique. Auto-correlation matrix $(H(x, y))$ that can be used to classify a point as a corner feature has been defined in earlier section. Let ς_1, ς_2 be two eigen values of the auto-correlation matrix H such that $\varsigma_1 > \varsigma_2$. Points for which both ς_1, ς_2 become greater than a pre-defined threshold are said to be a Good Corner Points.

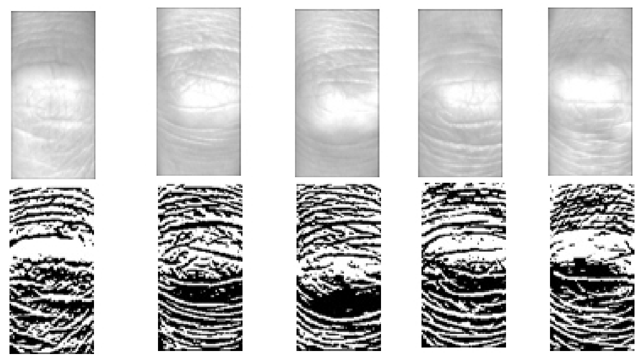
VIII. Matching

This section discusses the matching technique of the proposed biometric system. LK Tracking has been used to track corner points of query image in enrolled images. Let Q be the preprocessed query image, T be the preprocessed enrolled image and S be the set of corner features extracted from Q such that,

$$S = (p_1, p_2, p_3....p_n)$$



(a) Palm Images



(b) Knuckle Images

Fig. 5: Some Enhanced Images

Algorithm 4.3: $ExtractCornerFeatures(T, Thr)$
Input: T: Query Enhanced Image and threshold
Output: S: List containing coordinates of Good Corner Points
h = height of T
w = width of T
for $i \leftarrow 0$ **to** $(h-1)$ **do**
    for $j \leftarrow 0$ **to** $(w-1)$ **do**
        Calculate auto-correlation matrix $H(i, j)$
        Find ς_1, ς_2 the two eigen values of the $H(i, j)$
        if $(\varsigma_1 > Thr \,\&\&\, \varsigma_2 > Thr)$ **then**
            Add point (i,j) to list S
return S

---

with each corner feature point/pixel p_i represented as

$$p_i = (x_i, y_i)$$

LK tracking outputs an approximate location of point $p_i(x_i, y_i)$ in the preprocessed enrolled image along with some tracking error E_i as defined below. Let the tracked location be $p_i'(x_i', y_i')$. Then point p_i is said to be matched with p_i' if following conditions are satisfied :

1) Euclidean distance between p_i and p_i' is less than distance threshold (TH_{dis}), i.e, $\|p_i - p_i'\| \leq TH_{dis}$ [27].

2) Tracking error E_i is less than a tracking threshold (TH_{te}), that is, $E_i \leq TH_{te}$ [22].
3) Hamming distance between the Gaussian Response code of the corresponding neighborhood pixels of p_i and $p_i^{'}$ is less than a predefined threshold (TH_{ham}). Matching assumes a $K \times K$ square window, where value of K has been determined experimentally. This step has been described in Algorithm 4.4

Algorithm 4.4:$MatchPoint(Q, p_i(x,y), T, p_i^{'}(x_1,y_1))$
Input: Q: Enhanced Query Image
Input: T: Enhanced Enrolled Image
Input: $p_i(x,y)$: pixel with coordinates (x,y) in Q
Input: $p_i^{'}(x_1,y_1)$: pixel with coordinates (x_1,y_1) in T
Output: $isMatched$: matching result of two points $p_i \in Q$ and $p_i^{'} \in T$. TRUE=Matched, FALSE=Not Matched
Values of l, d, TH_{ham} are evaluated experimentally over a validation set.
$isMatched$ = TRUE
for $k \leftarrow -l$ **to** l **do**
    for $r \leftarrow -l$ **to** l **do**
        $P_x = (x+k, y+r)$
        $P_y = (x_1+k, y_1+r)$
        v_1 = $GRC(P_x, Q)$
        v_2 = $GRC(P_y, T)$
        if $H(v_1, v_2) > TH_{ham}$ **then**
            $isMatched$ = FALSE
        $k = k + d$
    $r = r + d$
return $isMatched$

Several threshold values TH_{dis}, TH_{ham} and TH_{te} are obtained experimentally by optimizing result over a small validation set. Mathematically, matching score (dissimilarity measure) is calculated as follows.

$$score = 1 - \frac{m}{n}$$

where m is the number of good feature points in query image Q which are correctly matched ("satisfying above conditions") in preprocessed image T and n is the total number of good feature points in query image Q.

IX. Experimental Results

The performance of the proposed system has been discussed in this section. Some publicly available databases such CASIA-PALM [32], PolyU-PALM [33] and PolyU-KNUCKLE [34] have been used to measure the performance. Several parameters that are required to evaluate the score are estimated by optimizing the result over a small subset of actual database called validation set. In this work score level fusion is preformed.

1) **Palm Database:** CASIA-PALM database consists of 5502 hand images of 312 individuals where 8 images from each hand have been collected from each subject. Four images are considered as training and other four are considered as query images. We have used another palmprint database PolyU-PALM, which has 7752 hand images obtained from 193 individuals. It contains 20 images of each hand of each subject over two sessions. For training, first ten images are considered while remaining 10 have been used for testing.
2) **Knuckle Database:** PolyU-KNUCKLE is a Knuckleprint database. It has a total of 7920 knuckle images collected from 165 subjects. Images have been collected in two sessions. In each session, they have collected 6 images from a finger of each subject. Images of the first session have been considered as training images while of second session images are used for testing purpose.

Performance of the proposed biometric system is evaluated by correct recognition rate (CRR) for identification and equal error rate (EER) for verification mode as defined in [27].

A. Results on Palm Databases

The proposed system has achieved a CRR of 99.79% with an EER of 3.37% over PolyU-PALM database. The accuracy is observed as 96.97% and the ROC curve is shown in Figure 6(a). The CRR got saturated (*i.e.* 100%) when top 16 best matches are considered. A CRR of 99.91% with an EER of 0.67% has been obtained over CASIA-PALM database. The accuracy is observed as 99.41% and the ROC curve is shown in 6(b). The CRR got saturated (*i.e.* 100%) when top 83 best matches are considered.

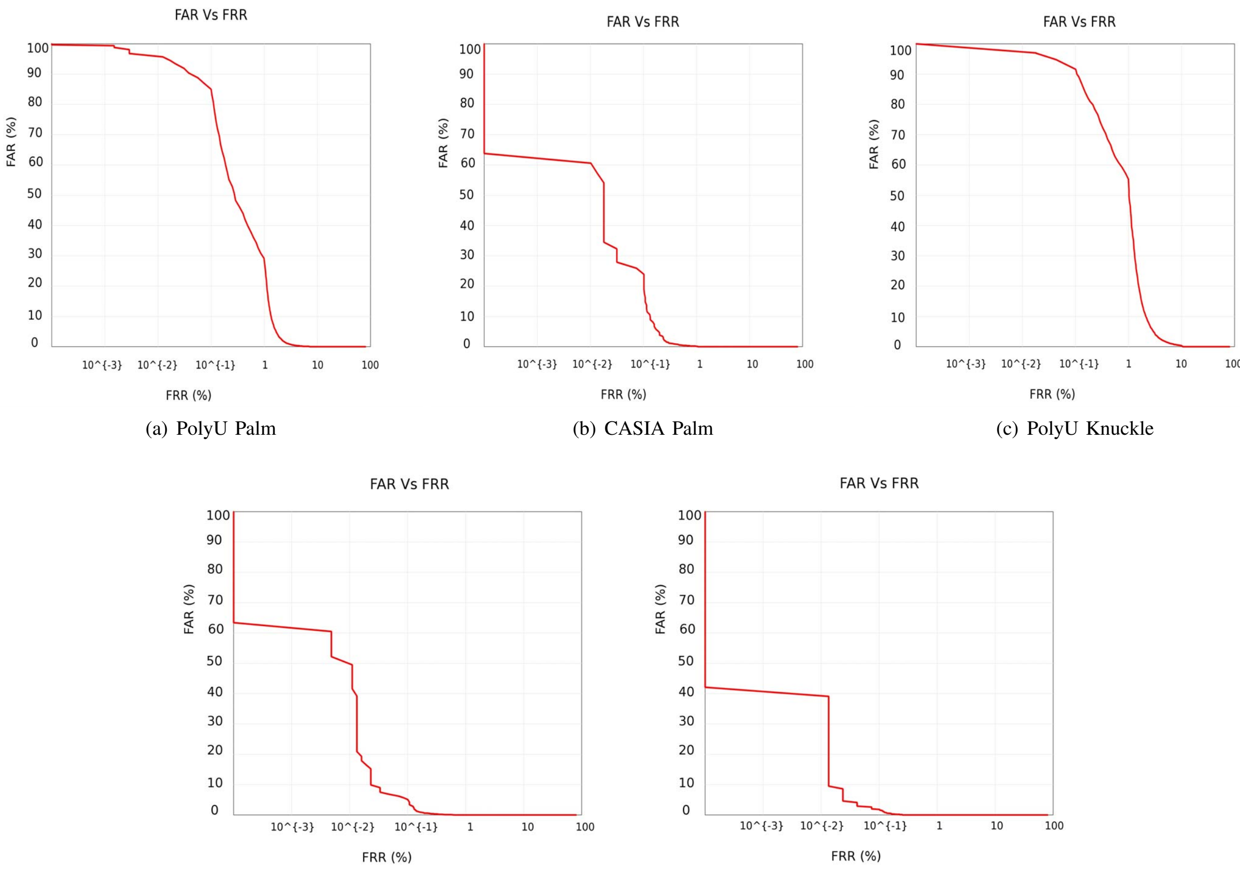
B. Results on Knuckle Database

The proposed system has achieved an CRR of 97.65% with an EER of 5.04% over PolyU-PALM database. The accuracy is observed as 95.51% and the ROC curve is shown in 6(c). The CRR got saturated (*i.e.* 100%) when top 16 best matches are considered.

C. Fusion Results

Score level fusion has been used to design a multimodal system. Equal weight has been given to each score (*i.e* Sum Rule). Two manually self created chimeric databases have been used for performance analysis of the proposed system.

1) **First experiment**
PolyU-PALM and PolyU-KNUCKLE database are considered for this experiment. 386 subjects have been randomly selected from each of these databases. For each subject, 6 images are randomly chosen from training and testing session to form the training and testing set.The EER of this system is found to be 0.44%. The ROC curve has been shown in Figure 6(d). Accuracy of the system is found to be 99.58%. The proposed system achieves a CRR of 100% for the top best match.
2) **Second experiment**
In second experiment PolyU-KNUCKLE database and CASIA-PALM database are used. To make the training and testing set, 4 images from 566 subjects are chosen



(a) PolyU Palm (b) CASIA Palm (c) PolyU Knuckle

(d) FUSION : Palm(PolyU)+Knuckle (e) FUSION : Palm(CASIA)+Knuckle

Fig. 6: ROC Curves for the proposed System

randomly from the training and testing session of PolyU-KNUCKLE and CASIA-PALM database. For this experiment, the EER is found to be 0.31%. The ROC curve of this experiment is shown in Figure 6(e), where an accuracy of 99.72% has been achieved. It is found that the CRR of the proposed system is 100% for the top best match.

X. Conclusion and Future Work

This paper has proposed a multimodal recognition system which is based on palmprint and knuckleprint images. It has defined a measure termed as Gaussian Response Code (GRC) to encodes an image region into a 8-bit code and has been used to track good corner features in both palmprint and knuckleprint images. The proposed system works on edge-maps and hence is invariant to illumination variations. The system has been tested over publicly available palmprint and knuckleprint database.

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