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Palm Print Recognition based on Local Binary Pattern

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Abstract- **Automatic person verification has become one of the most crucial problem in networked society. Authorized providing access to a person is a very challenging task. Biometrics has emerged as an important as well as an effective solution to resolve all these issues. The Biometrics identification of an individual is can be done by physiological or behavioral characteristics, where the palm print image of an individual can be captured by using sensors and is one of among physiological characteristics of an individual. Palm print recognition system is most promising to recognize an individual based on statistical properties of palm print image. In this paper we discusses a new method and its related analysis that based on palmprint verification using local binary pattern (LBP) to capture the palmprint texture. Experimental results shows that this technique is simple, highly accurate and takes less time to process the palmprint image. The experiment is carried out by using MATLAB software image processing toolbox.**

***Keywords* – Palm print, Local Binary Pattern, Chi-squared test, Pearson's correlation test, Classification, Region of interest**

I. INRODUCTION

There are many security concerns regarding access control of any system used to verify whether a person is genuine or not. Most of the available access control methods use Knowledge Based Identification System, which requires a user to enter a PIN or password for authentication. But, this technique faces a problem in case of forgotten or stolen passwords as it is difficult to remember different passwords for different systems. However, biometric Identification system is available for overcoming this limitation. Biometrics includes the use of physiological or behavioural characteristics to verify a person. Physiological characteristics can be fingerprints, facial features, iris, hand geometry, DNA, palmprint and odour/scent. On the other hand, behavioural characteristics are related to the behaviour of a person like typing rhythm, gait and voice. Selection of biometric depends upon various factors like universality, uniqueness, permanence, measurability, performance and acceptability of biometric.

Fingerprint verification has attracted a considerable amount of attention for the last 25 years. However, some people do not have clear fingerprints because of physical work, problematic skin or accidental reasons. For such cases, fingerprint becomes hard to extract for verification. Iris and retina are other powerful biometrics that gives high accuracy but a high cost input device is required, making it an expensive verification system. Recently, many researchers have been involved in face and voice verification but these systems are not able to give satisfactory performance and are affected by ageing, emotions etc.

Compared with other biometrics, palmprint verification system has several advantages low resolution imaging, low intrusiveness stable line features high user acceptance low cost capturing device rich texture feature. Palmprint is a new research area as compared to other biometrics, so there exist many techniques which are still unexplored. Palmprint is the large inner surface area of the palm which contains principal lines, wrinkles and ridges. Palm prints of different persons are easily differentiable by considering geometry, line, texture, point and statistical features. Sometimes a combination of features is used to make a system highly accurate.

In texture based approaches have been used employing Gabor filters to extract the phase information from a palmprint image. Present a minutiae based palmprint recognition system that can realize unrestricted matching between the complete palmprint and misshapen palmprint, thus being able to identify the owner of the palmprint. Most authors focus on palm lines as an important feature of palmprint image. Palm line includes principal lines and wrinkles but, principal lines get more attention because of

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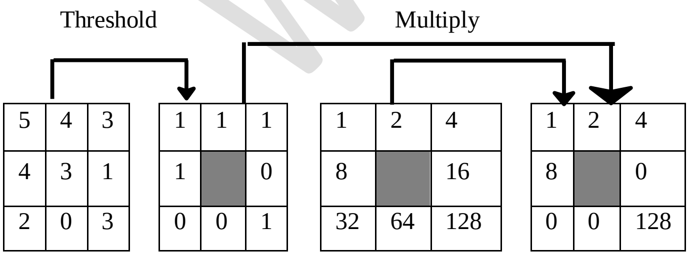
their stable and highly distinctive nature. These can easily be marked in bad illumination conditions, compression and noise. Considering all these characteristics designed palmprint verification based on principal lines through feature extraction technique using modified finite radon transform and have devised a personal Identification system for inked palmprint images. They first extract a set of features along prominent palm lines from palmprint image and then take a decision by calculating the match score between the corresponding set of feature points between two different palmprint images. devised a system which uses two novel characteristics in palmprint verification, These are datum point variance and line feature matching have proposed palmprint Identification using boosted local binary pattern. Palmprint area is scanned with a scalable sub-window from which local binary pattern histograms are extracted to represent the palmprint features.

In this paper, we investigate the match of palmprint by using texture as a feature. Texture is represented as a local binary pattern which is a simple and efficient texture operator. Section II presents a brief introduction on local binary pattern. Section III describes the complete methodology for palmprint matching system. In Section IV, experimental setup and results are discussed. Section V describes the result analysis. Section VI concludes the paper.

II. LOCAL BINARY PATTERN BASED FEATURE

Local Binary Pattern (LBP) is a feature extraction technique that gives satisfactory results in various computer vision based applications. The LBP operator forms labels for the image pixel by thresholding the 3x3 neighborhood of each pixel with the center value and storing it as a binary number. This is shown in Figure 1. The maximum value that a center pixel can have is 256. The histogram of these 256 labels is used as a texture descriptor.



LBP=1+2+4+8+128 =143

Fig. 1. Calculating the original LBP code of 3×3 neighborhood

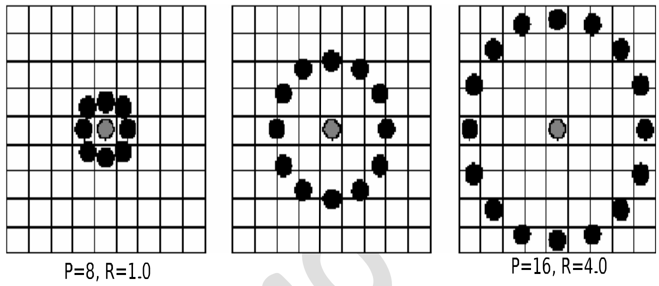


Fig. 2. Example of circular neighborhood at different radius

This operator can be extended to different neighborhoods of different shapes. Circular neighborhood and bilinear interpolation [14] allow any radius (R) and number of pixels (P) in the neighborhood for any center pixel as shown in Figure 2. For a circular neighborhood, the coordinates of neighbor pixel (x_p, y_p) are given by:

$$x_p = x_c + R\cos\left(\frac{2\pi p}{P}\right) \qquad (1)$$

$$y_p = y_c - R\sin\left(\frac{2\pi p}{P}\right) \qquad (2)$$

Here, $p = 0, 1, 2 \ldots..(P - 1)$ and (x_c, y_c) are the co-odinates of the center pixel. If the neighborhood does not fall exactly

A. Database

on the pixels, then neighborhood pixel coordinate are estimated by bilinear interpolation. The local primitives detected by LBP include spots, flat areas, edges, edge ends, curves and so on.

Another extension of the local binary pattern is the uniform LBP pattern, introduced by Maenpaa and Pietikainen. These patterns are called uniform because they contain at-most two one-to-zero or zero-to-one transitions in the circular binary code e.g. 00000000, 1110011, 00011111.

In this paper, we obtain palm line texture information using the uniform local binary pattern $LBP^{u}_{P,R}$ where P is circular neighborhood, R is the radius and u stands for uniform pattern. All non uniform patterns are defined using a single value

Histogram of the image $L(x, y)$ is constructed as:

$$H_i = \sum_{x,y} I\{L(x,y) = i\} \quad , i = 0 \ldots\ldots\ldots, n-1 \qquad (3)$$

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where, *n* is the number of different values produced by the LBP operator. The histogram contains information about the distribution of edge patterns in the palm image.

III. PROPOSED METHOD

The palmprint matching system starts with acquiring an input image of the hand using a palmprint scanner. Identity verification using the proposed method is shown in Figure 3.

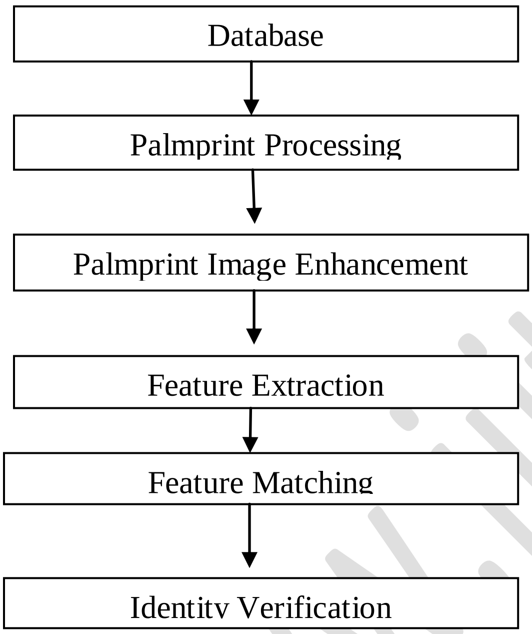

Fig. 3. Flowchart of Palmprint Matching System

For our experiments, we have taken palmprint images from the PolyU palmprint database. From this database, we have used five palmprints each of fifteen users. This gives us 75 samples. For matching, 128 combination pairs of the same user and 105 combination pairs of different users are taken. This gives us a set of 233 pairs.

B. Palmprint Preprocessing

Palmprint preprocessing is done to extract the region-of-interest (ROI) of the palm for feature extraction. The ROI is determined so that there is maximum variation among different users and minimum noise due to low picture quality. Palmprint image preprocessing highly depends upon the database of the palm images. We have taken a peg fixed database. In this type of database, users are asked to place their fingers at positions specified by pegs so as to reduce the rotation of the hand.

The ROI extraction is divided into three major steps- (i) Binarization (ii) Boundary tracing (iii) Region-of-interest detection. These are shown in Figure 4.

1) Binarization: Binarization converts a gray scale image into a binary image [17]. There is a clear contrast between the background and hand images. Thus, a global thresholding can be applied to binarize the image. For any input image $\boldsymbol{I}$ of size $M \times N$, threshold value can be determined by using formula:

$$G_{-threshold} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} I(i,j)}{MxN} \qquad (4)$$

where, $\boldsymbol{I}(i,\boldsymbol{j})$ represents the intensity value at any pixel location $(i,\boldsymbol{j})$. The pixel intensity value of binary image B is computed using formula :

$$B(i,j)) = \begin{cases} 0 & if\ I(i,j) \leq G_{-threshold} \\ 1 & \text{otherwise} \end{cases} \qquad (5)$$

where, intensity value 0 represents black and 1 represents a white pixel. Binarization is shown in Figure 4(b).

2) Boundary Tracing: Boundary of the hand image is traced by using a boundary tracing algorithm [18] on the binarized image as shown in Figure 4(c). This algorithm traces the exterior boundaries of objects and returns row and column coordinates of each boundary pixel for each object.

3) Region of Interest Detection: Reference point is used as starting point of the rectangular region of interest. This reference point is extracted by the help of valley points in the boundary of the palm image. To get valley points, *x*-coordinate value of boundary pixels traced and found local maxima or minima points which acts as valley points. Only three valley points (*V*) fits in our requirement. So, remove other valley points if exist by setting a distance parameter in between extracted valley points. These valley points are represented by the help of green dotes in Figure 4(d). To calculate the coordinate value (x, y) of reference point:

$$X = max(V_X); \qquad (6)$$

$$Y = min(V_y); \qquad (7)$$

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Where, V_x and V_y are the x and y coordinates of V. The reference point (x, y) shown in Figure 4(d) as a blue dot. With the specified height and width, we can extract a rectangular region of the palm that is used for further processing. This is shown in Figures 4(e) and 4(f).

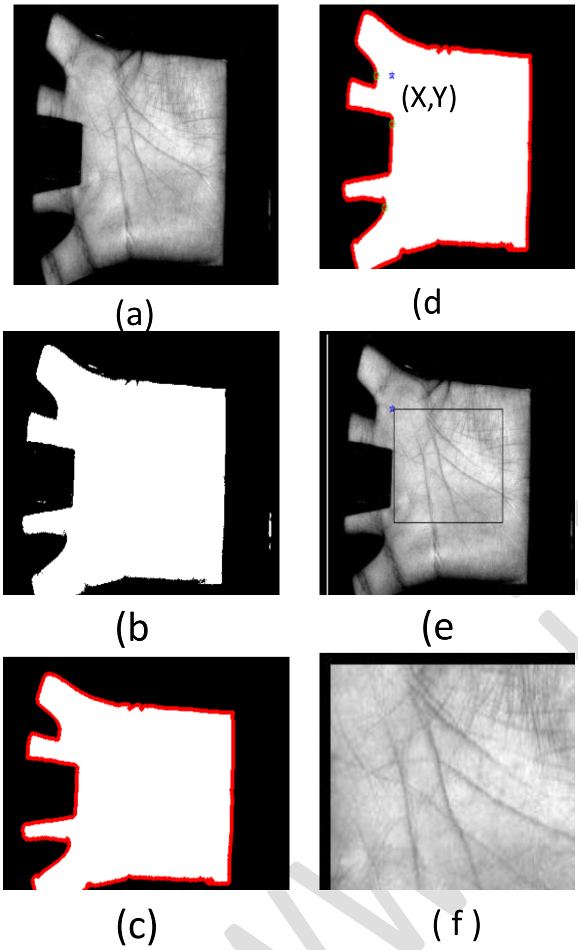

Fig.4. Palmprint Image Preprocessing
(a) Input image (b) Binary image
(c) Traced boundary of binary image (d) Extract reference points
(e) Specified region of interest (f) Extract region of interest

C. Palmprint Image Enhancement

Palmprint image enhancement techniques are applied to make palm lines more clear and visible. These techniques are also able to remove local noise and thin lines of the image. To perform smoothing, a 2-D averaging filter is used. Each image pixel is replaced with the average of the pixel values in its 3x3 neighborhood.

D. Palmprint Image Feature Extraction

Feature extraction is based upon the texture of enhanced palmprint image calculated using Local Binary Pattern as discussed in Section II. The extracted and enhanced palm-print image is processed as follows:
1) Take enhanced palmprint image as input and compute the local binary pattern by specifying neighbor set and radius to form circular neighborhood.
2) Perform range normalization to change the range of the pixel intensity value and to achieve consistency among the dynamic range of the intensity value.
3) Generate the LBP histogram.
4) Store the LBP histogram as a feature vector as shown in Figure 5.

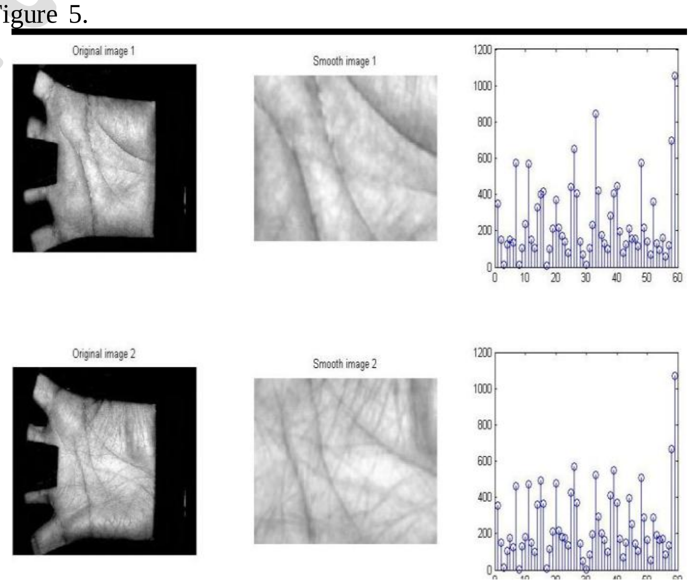

Fig. 5. Feature Extraction using Local Binary Pattern

E. Feature Matching

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To match the different sets of LBP histograms, we have used Chi-square test and Pearson correlation test.

1) Chi-square test: Chi square test is used to measure the dissimilarity between two different feature sets. It is calculated by using the formula:

$$X(H^P H^G) = \sum_{i=0}^{l} \frac{\left(H_i^P - H_i^G\right)^2}{H_i^P + H_i^G} \qquad (8)$$

where, *P* represents the observed histogram data (input image) and *G* the expected histogram data (reference image). If the value of Chi-square test is closer to zero then there is high similarity among the feature set.

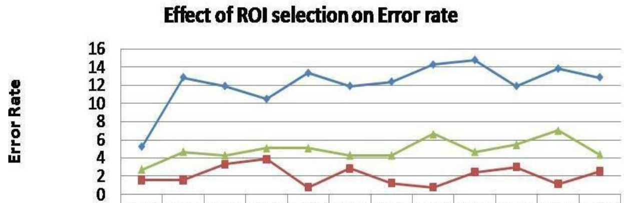
2) Pearson's correlation test: Pearson's correlation is another similarity measure which evaluates the degree of correlation between the input histogram and reference histogram. It is calculated by using formula:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \qquad (9)$$

where, x and y are the different feature sets with n input values, $\bar{x}$ and $\bar{y}$ are the corresponding means of x and y and $\boldsymbol{r}$ is the value of similarity between x and y.

F. Identity Verification

In our experiment, identity verification is a two class problem (genuine or imposter). The Classification task can be treated as constructing a decision boundary in feature space using the results of either Chi-square or Pearson's correlation test. Discriminant function analysis between the two class dataset is able to create a decision boundary among the feature space.



	152*100	152*120	152*140	162*100	162*120	162*140	172*100	172*120	172*140	182*100	182*120	182*140
Linear	5.24	12.8	11.9	10.4	13.3	11.9	12.3	14.2	14.7	11.9	13.8	12.8
Quadratic	1.56	1.56	3.3	3.86	0.78	2.82	1.26	0.78	2.43	2.99	1.17	2.51
Mahalanobis	2.73	4.69	4.3	5.08	5.08	4.3	4.3	6.64	4.69	5.47	7.03	4.38

Fig.6. Effect of ROI selection on Error rate

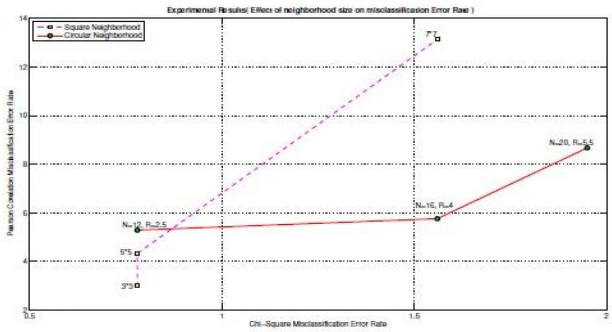


Fig.7. Effect of LBP neighborhood size on Error rate

With 233 combination pairs, different neighborhood and ROI selection conditions are considered. Experiments are performed to compare the results for palmprint matching. These experiments are carried out to check the accuracy level at different parameters. Chi-square and Pearson correlation are computed for each palm pair. Discriminant analysis is done by considering linear, quadratic and mahalanobis decision boundaries.

A. Selection of ROI

In this experiment, different sizes of ROI are extracted to analyse which Palm region gives high accuracy. The ROI size is varied from 152 × 100 to 182 × 140 by taking various height and width combinations as shown in figure 6.

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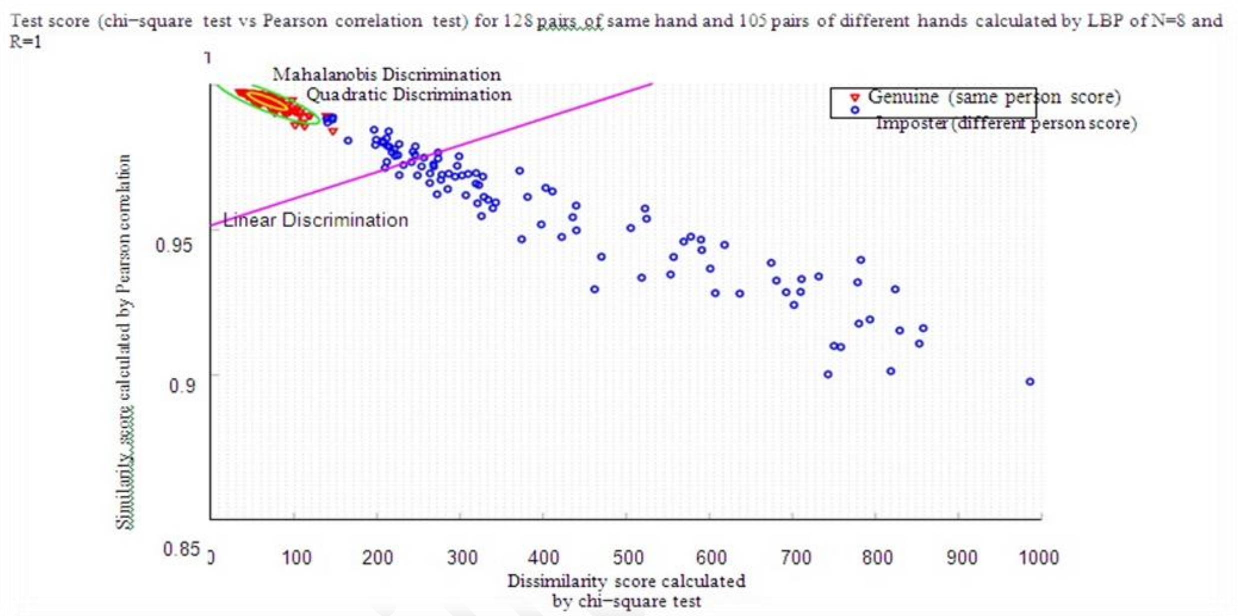

Fig.8. Test Score (Chi-square vs Pearson correlation) results for 128 pairs of same hand and 105 pairs of different hands calculated by LBP of N=8 and R=1. The line segments represent the different Discriminant axes.

B. Effect of LB neighborhood

In this experiment, misclassification error rate is tested using different radius and window sizes for circular and square neighborhoods. For square neighborhood, use window sizes 3×3, 5×5 and 7×7. For circular neighborhood, it is tested for twelve neighbors at radius 2.5, sixteen neighbors at radius 4 and twenty neighbors at radius 5.5. This is shown in Figure 7.

V. RESULT ANALYSIS

Experiments are performed to make an analysis for the optimal palm region and LBP neighborhood. We investigate the matching accuracy for the optimal parameters. The performance of the proposed method in term of accuracy is obtained and compared with some recent methods.

A. Results for proposed method

Result for different ROI selections are shown in Figure 6. It is observed that the quadratic decision boundary performs better than linear and mahalanobis decision boundaries. We see that quadratic decision boundary gives lease error rates for ROI sizes 162 × 120 and 172 × 120. Thus, it can be argued that these two sizes are optimal ROI selection for this database. Result of best LBP neighborhood are shown in Figure 7. As we increase the size of radius and number of neighbors for circular neighborhood and square window repective error rates also increases. However, increasing radius and window size also increases the feature vector size and time complexity.

The score of genuine and imposter data using Chi-square dissimilarity test and Pearson correlation similarity test are distributed along 2-D axes to clearly depict the discrimination among them. As shown in Figure 8, quadratic decision boundary best discriminates the genuine distribution from the imposter distribution as compared to

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linear and mahalanobis. Figure 9 depicts the corresponding false acceptance rate (FAR) and false rejection rate (FRR) curves at different threshold value. Common area between the curves depicts the misclassification error. As can be seen, it is very small.

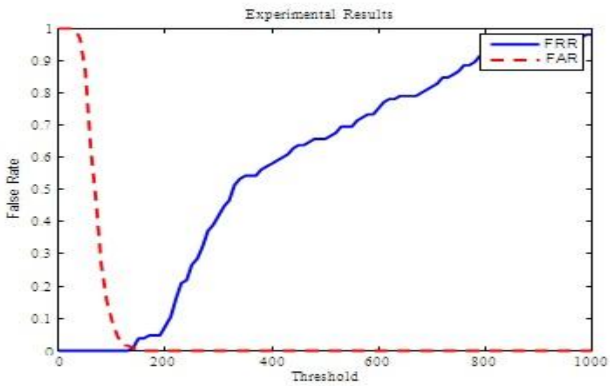

Fig. 9. FAR and FRR curve of proposed system

B. Performance Comparision

For the purpose of comparison, matching accuracy obtained using proposed method compared with the reported method in [10] and [19] are listed in Table I.

Table I
COMPARISION OF PALMPRINT MATCHING ACCURACY

Method	**Features**	**Accuracy**
Proposed Method	Palm-texture	99.22%
Method [10]	Feature points	94.3%
Method [19]	Eigen Palms	99.15%

VI. CONCLUSION

This paper explores the use of local binary pattern for palmprint verification based on texture. This indicates that feature is extracted by local binary pattern. Chi-square dissimilarity test and Pearson correlation similarity test calculate the matching score among two different feature sets. Discrimination function evaluates the threshold value which decides the class of the input image. Experimental analysis for variation in ROI selection show that ROI sizes 162×120 and 172×120 are optimal for this database. Error rates are reduced if we choose LBP neighborhood of minimum window size 3×3. Analysis on different types of discrimination functions shows that quadratic decision boundary gives best results. The system achieves an accuracy of 99.22% with 0.78% misclassification error rate.

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