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An Approach to Improve Palmprint Recognition Accuracy by using Different Region of Interest Methods with Local Binary Pattern Technique

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Abstract

Objective: To extract the Region of Interest (ROI) of palmprint image by using appropriate methods and to improve the accuracy of palmprint recognition system. **Methods/Statistical Analysis**: This piece of work is primarily addressing the different mechanisms for extracting ROI area. The techniques like Competitive Hand Valley Detection (CHVD), and Euclidean Distance (ED) were applied as the part of pre-processing, while the Feature Extraction mechanism LBP was utilized to extract the texture feature from different type of ROIs of palmprint image. **Findings**: The experimental results showed that *CHVD* with LBP gave best result with high accuracy reached to 96.10534% and Equal Error Rate (EER) of 3.894661%, while in ED the best result showed accuracy reached to 88.23611% and EER of 11.76389%. **Application/Improvements:** The study mainly concentrated on developing palmprint authentication system with less EER and high accuracy.

Keywords: Analysis, Competitive Hand Valley Detection (CHVD), Euclidean Distance, Local Binary Pattern (LBP), Palmprint Recognition

1. Introduction

Today, personal identification playsan active research and applications in our daily life like banking, immigration, and access control, ID card, passport office and country borders etc. Recently, the biometric application (identification or verification) has widely used and majority of research studies have conducted in the field of security system with different technologies (modalities or traits) such as fingerprint, iris, palmprint, face, retina etc[1]. Biometric is the automatic system which is used to recognize the persons by their characterizations (behavioral and physical)[2]. The main objective of any biometric system is to achieve low cost, less error rate, speed in performance and high accuracy.

There are two types of palmprint which called high resolution and low resolution. Each type is suitable for different applications. High resolution images are used for forensicapplication[3] while low resolution images are used for access controls application.

Palmprint trait has a rich of information which is useful for identification and verification propose. Different types of feature can be extracted from high and low resolution palmprint images. The features from high resolution images include Minutiae feature, Ridges features and Singular point feature[4–5]. Whereas, the features from low resolution images include Principal line, Texture feature, Palm-crease, Wrinkles and Statistical features. All these features present on the surface of palmprint images.

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The methods of palmprint can be classified into different classes depending upon verification and identification. The methods used in verification system include Line based methods, subspace based methods and statistical based methods. Line-based methods are focused on edge detectors to extract the palm lines from the palmprint images such as mention in[6–14]. Matching of these lines can be made either directly or indirectly by using different matching format. Subspace based methods, PCA method, LDA method and ICA method were studied in earlier works[15–18] other methods like wavelets, Gabor, DCT and Kernels were mentioned in[19–22].

Statistical methods are either local or global. In the case of Local the images should be transformed to another domain and then divided into several small regions[23–27]. The means, standard divisions and variances of each region were calculated and stored as features. Some of researchers used Gabor, wavelets and Fourier transforms[28–30]. Another researcher used Local Binary Pattern (LBP) histograms as features[31]. Whereas, some of them used global statistical methods like Moments, centers of gravity and density as mention in[31–36].

The remaining sections of the paper are discussed the methodology system which includes the preprocessing, ROIs methods, feature extraction, matching and decision that covered in section 2. The results and discussion are given in details in section 3. Section 4 exhibits the conclusion and future work.

2. Methodology of the System

In this section the methodology of the palmprint recognition system is discussed. The ROI from palmprint images was extracted by two ways called as CHVD, and ED. The ROI was passed to feature extraction techniques to extract the texture feature by using LBP technique, and then the feature reduction technique was utilized to reduce the dimensionality by PCA method. After that the features were stored as data template which used for matching purposes. This section was divided into different sub-sections. Section 2.1 which covers the ROI methods in details, section 2.2 which discusses LBP feature extraction methods, section 2.3 which represents the matching process and section 2.4 which shows the decision. Figure 1 shows the block diagram of methodology of plamprint recognition system.

2.1 ROI Extraction Methods

The ROI refers to a subset of all the data used in an observation. In palmprint ROI is the data of two- dimensional and defines as rectangular area on the hand surface. It is a small area which includes more information like Minutiae, Principal line, and the key point. The key points involve an end points or a branch points[37] which needed in the process of identification or verification. There are many techniques utilized to extract the ROI from palm image such as CHVD and ED. There are two general steps performed before making ROI algorithm

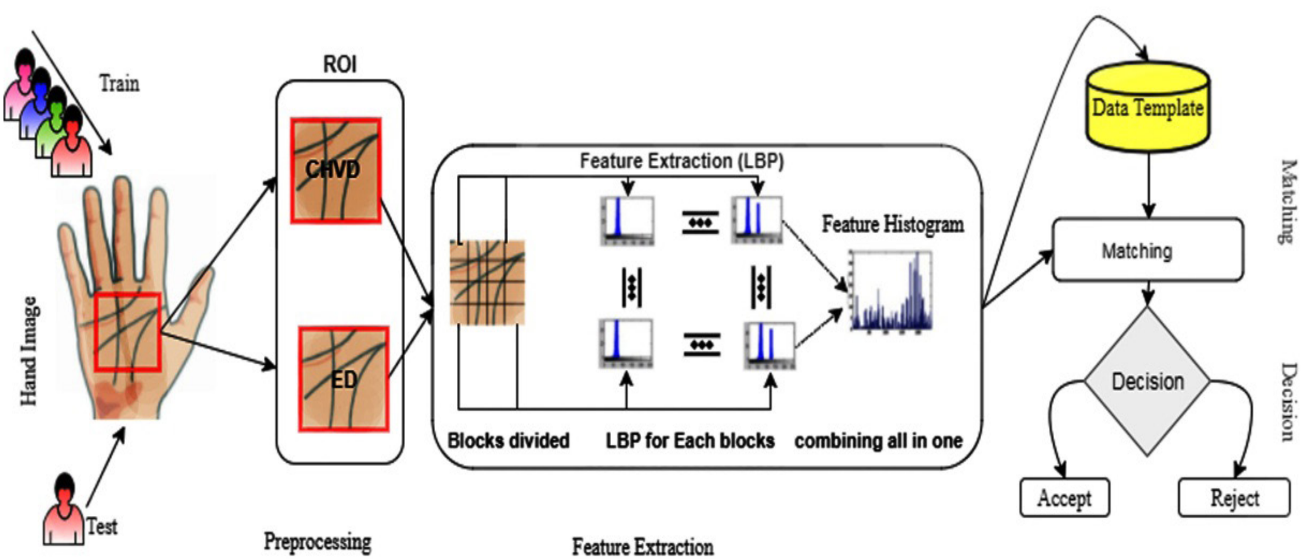


Figure 1. Methodology system of palmprint recognition system.

namely: image Binarization and boundary extraction which include in the pre-processing stage as shown in (Figure 2).

Image Binarization: It is the process of converting gray scale images into black-and-white image based on threshold value by multiplying a coefficient α with the greatest possible values of the scale of gray used ($\theta = \alpha * 2n\text{-}1$) where n is a fine gray scale used and θ is the threshold value (T). The value is changed for each pixel in image by Eq. (1) where x is the pixel values at particular coordinates. 0 represents black and 1 represents white.

$$f(x) = \begin{cases} 0; x < \theta \\ 1; x \geq \theta \end{cases} \quad (1)$$

Boundary Extraction: Boundary objects can be generated from the black-and-white image by applying erosion operator on the matrix structuring element. The boundary of palmprint image can be obtained by Eq. (2):

$$Boundary\left(BW\ image\right) = BW\ image - \left(BW\ image\ \Theta S\right) \quad (2)$$

Where θ is an operator to perform erosion on a black and white image and S is the structuring element matrix which can be represented as shown in Eq. (3).

$$S = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad (3)$$

2.1.1 Competitive Hand Valley Detection (CHVD)

The CHVD algorithm was used to extract the ROI area from palm image based on four reference points which called the valley points that obtained by tracking the boundary and seeking the coordinates of all the points. The valley point is a pixel where most of its neighboring pixels are in the object area of palmprint. Figure 3 represents a block diagram of extracting the ROI using CHVD technique.

A CHVD algorithm checks whether a pixel included a valley point by different cases as discusses below:

Case 1: Putting four points test with same distance from pixel (current pixel) that will be checked whether

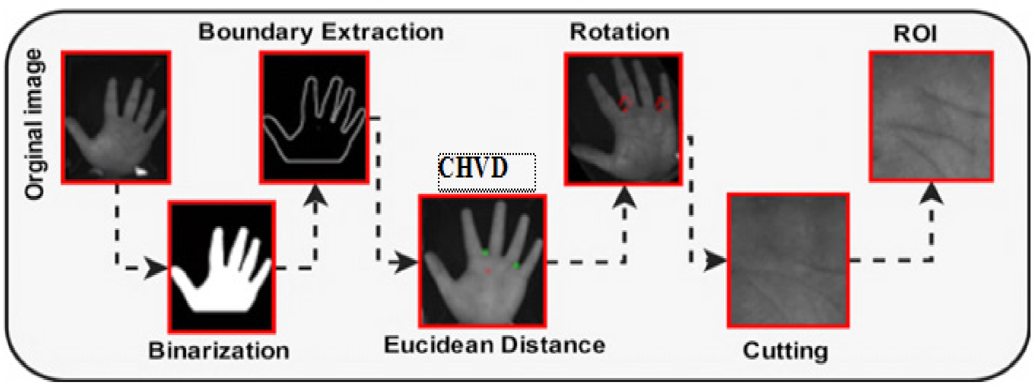


Figure 2. The main steps of palmprint pre-processing.

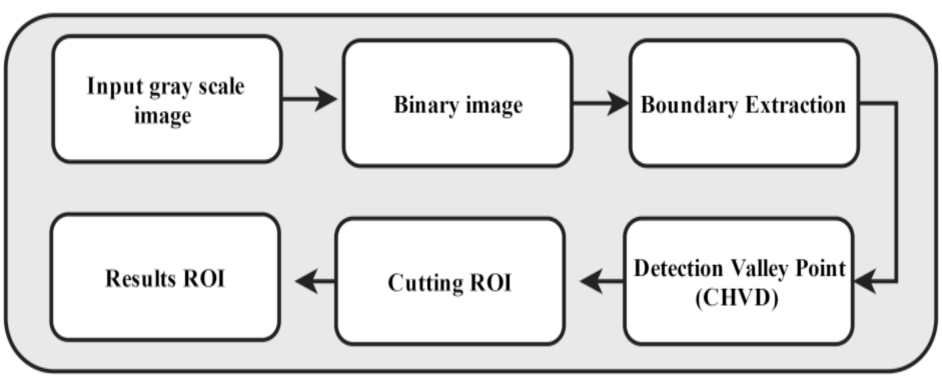


Figure 3. Block diagram of CHVD algorithm.

the pixel is a valley point. If one point is in the background while other areas are in the area then the current pixel palmprint be a candidate as a valley point and then do check the current pixel to the next condition, if not then the checks carried out for the next pixel,

Case 2: Test point increase to eight by the distance from the current $\beta + \alpha$ pixel. Make checks if at least one fruit or not more than four test points are in the background area and the rest are in the area palmprint the current pixel still be a candidate valley point and go to the next check,

Case 3: Test point increased to 16 with a distance $\beta + \alpha + \mu$ pixel (current pixel). If at least one fruit or not more than seven points are located on the background area and the rest are in the area palmprint the current pixel still be a candidate valley point and continued to check the latest condition, and

Case 4: Pull a straight line from the current pixel to the area of non-palmprint. If the line does not intersect with the current point palmprint area is considered as the valley point.

CHVD algorithm is based on the assumption that no person flexing his fingers over 120°[38]. The main problem in the CHVD algorithm is certain conditions can produce more than one candidate valley point. The solution is to select a point depend on the y axis value of the greatest or is at the bottom of the image of the four valley point $\{P_1, P_2, P_3, P_4\}$ two points taken as a reference point that is P_1 and P_2 as shown in Figure 4. ROI generation differs in terms of size and orientation. Then, the next step is to use the amount of the angle rotates ROI obtained from two reference points and changing all the ROI into a standard size using the Bicubic Interpolation. Figure 5 shows our developing of the Graphical User Interface (GUI) of automatic system for extracting ROI by using CHVD method.

2.1.2 Euclidean Distance

The idea of taking ROI using Euclidean Distance method is the same as CHVD technique. However, they differ by the way of getting the reference point. Figure 6 shows the block diagram of the ROI retrieval process by using Euclidean Distance.

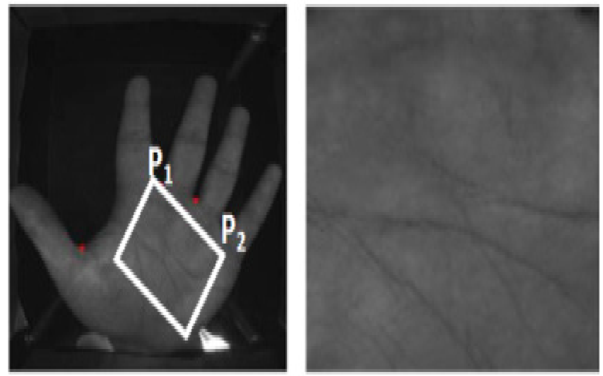


Figure 4. Making ROI process by CHVD.

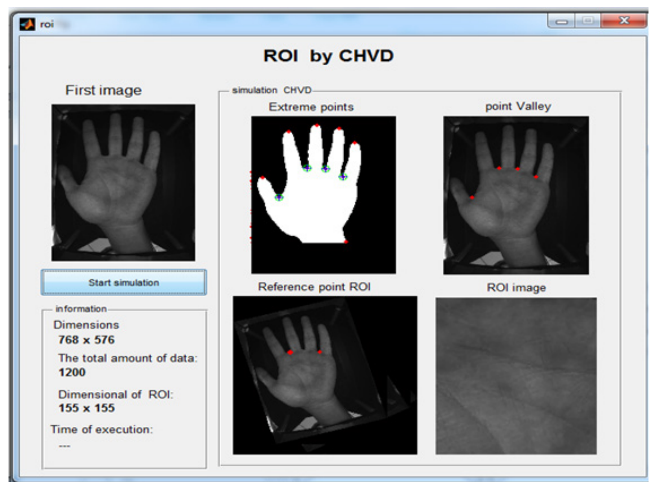


Figure 5. GUI of automatic ROI system by CHVD algorithm.

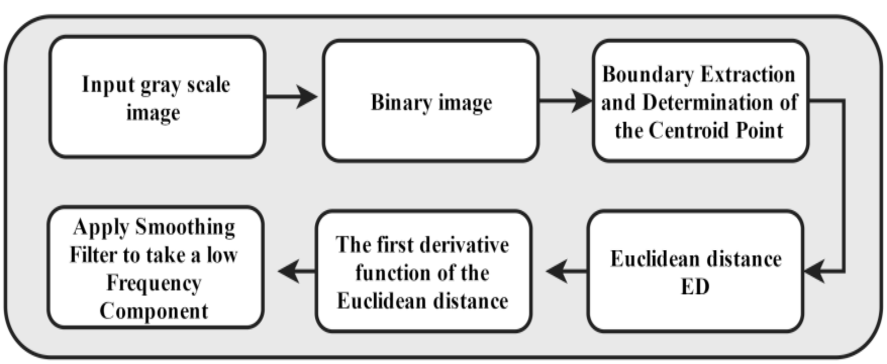


Figure 6. Block diagram of Euclidean distance.

The way to determine the centroid point of an object in a black-and-white image was to find the mean values of *x* and *y* of the overall coordinates point which is the location of the pixel that represents the object. The centroid coordinate point can be searched using Eq. (4).

$$x_{centroid} = \frac{1}{N}\sum_{i=1}^{N} x_i \text{ and } y_{centroid} = \frac{1}{N}\sum_{i=1}^{N} y_i \qquad (4)$$

Where x_i and y_i are the values of x and y at p $(x, y) = 1$.

The next step was to calculate the distance between each point on the boundary with its centroid point using the Eq. (5).

$$Dist(x, y) = \sqrt{(x - x_{centroid})^2 + (y - y_{centroid})^2} \qquad (5)$$

All the distance values resulting from Euclidean distance were calculated and plotted as shown in the Figure 7a.

The peak point shows the pixel location of the fingertips while the valley point indicates the pixel location of the valley point seen from its distance to the centroid point. To obtain the coordinates of the valley point, first find the first derivative of the Euclidean function and then mark the dots passing the zero on the y-axis (zero-crossing points). Figure 7b shows the first derivative value of the Euclidean function.

Both the vertex and valley points passed through the value 0 on the y-axis. However, in the graph above a lot of zero-crossing caused by the erratic contours of the palmprint image[39] so that the valley point location cannot be determined yet. This can be overcome by smoothing the graph by removing high frequency components and maintaining low frequency components. Figure 7c shows the results of the smoothing.

Valley point can be identified from the point that passed the value 0 on the y-axis and changed the sign from negative to positive. The reference point used is only the valley point between the index finger and the middle finger (V_1) and between the ring finger and the little finger (V_3) as shown in Figure 8.

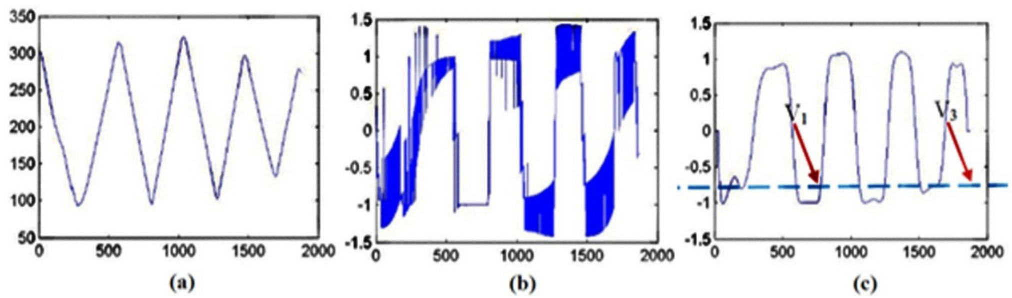


Figure 7. Extract ROI Method by ED: (a) Euclidean distance of each pixel within the boundary with the centroid, (b) First derivative value, and (c) smoothing value of First derivative graph.

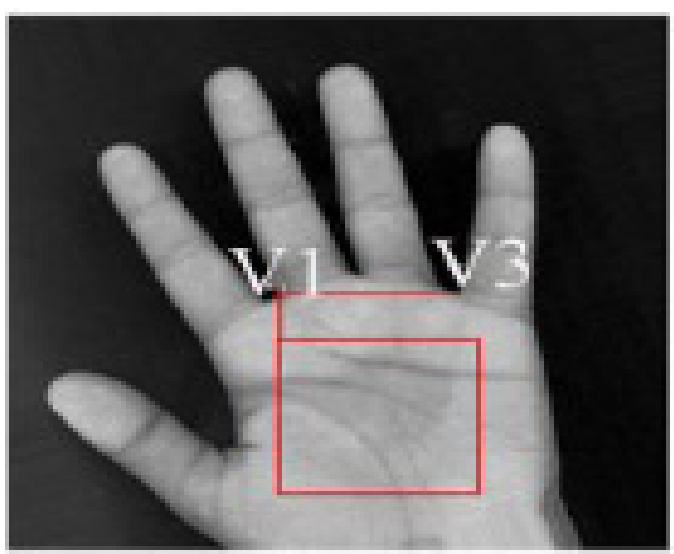


Figure 8. ROI detection of a palm image by ED.

Then point V_1 and V_3 were used to find the angle of rotation so that the ROI is the same for the hand with different orientations. The final step was to draw a straight line from point V_1 to point V_3 to form the ROI area. Figure 9 shows our developing system of extracting the ROI by Euclidean Distance method.

2.2 Feature Extraction using LBP

LBP operator considered as a texture feature and it is used for shape extraction of gray scale image. It refers to a binary code for an image-pixel and it provides us by information regarding the local neighborhood of that pixel. The principal LBP operator was given by[40]. The idea behind the LBP operator is to search a center

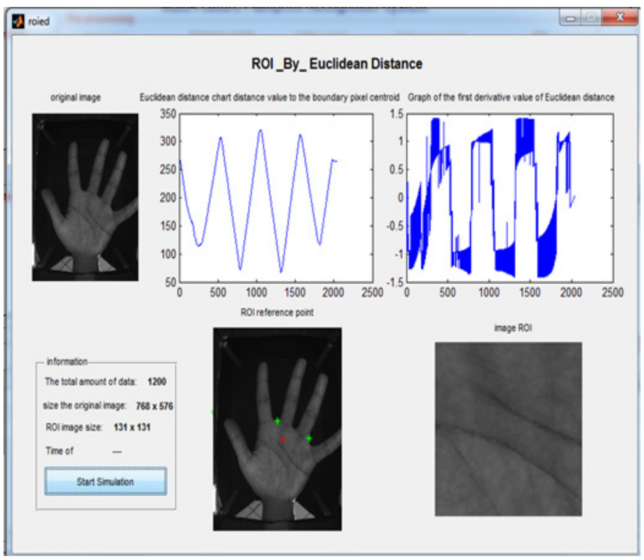


Figure 9. GUI of Automatic ROI system by using Euclidean Distance Algorithm.

pixel value of an image and take this value as threshold and check as below case:

$$LBP\_Binary\_Code = \begin{cases} 1; \ if \ neigborhood \\ \qquad\qquad pixel >= Threshold \\ 0; \ Otherwise \end{cases}$$

If neighbor pixel has higher value or equal to center pixel value, the pixel takes the value 1, otherwise it takes the value zero. The example of LBP and how to calculate a binary code is represented in Figure 10.

After that the LBP was extended to utilize neighborhoods of various sizes. In such case a circle is produced having radius R from the center pixel. P sampling points on the circle edge are determined and compared with center pixel value to find the values of all sampling points in neighborhoods for any radius and any number of pixels. Figure 11 demonstrates three neighbor sets for various values of P and R.

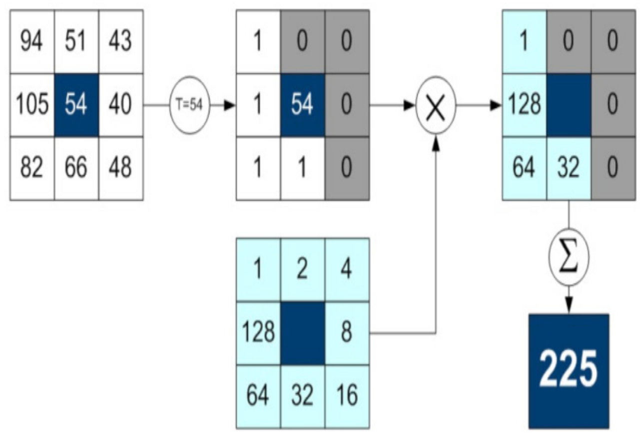


Figure 10. Stages of LBP calculation process.

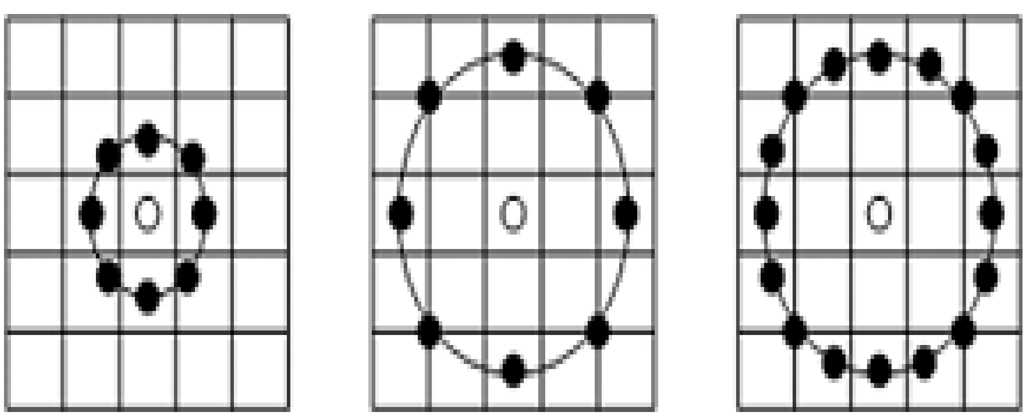


Figure 11. Circular (8,1), (8,2) and (16,2) neighborhoods.

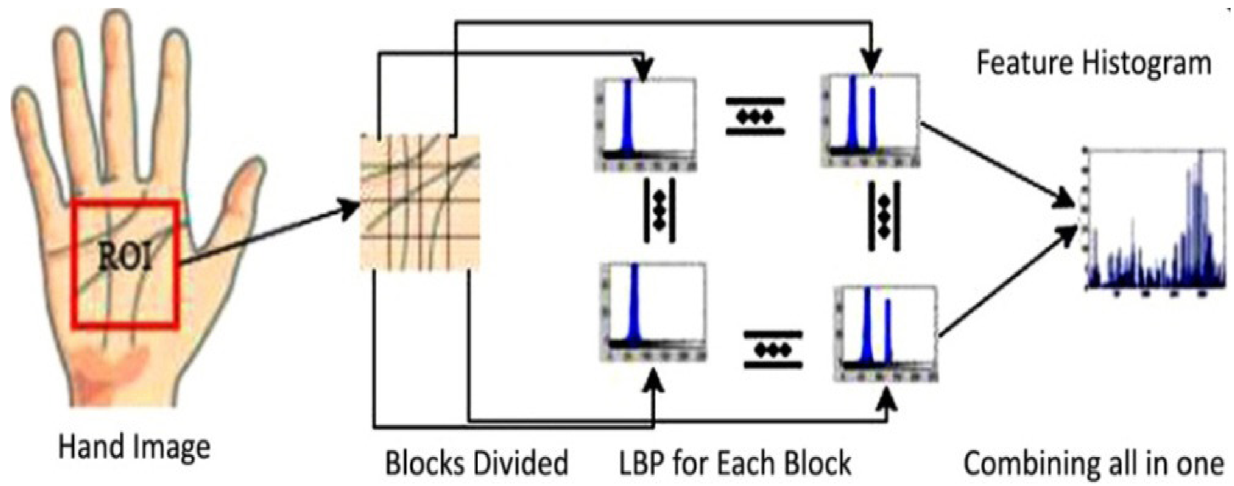


Figure 12. LBP of palmprint image with histogram of each block.

In the case of our work the LBP feature extraction was used to calculate the LBP for every pixel in the image. This occurred by divided the palmprint image into blocks or regions. Here the image was divided into (8 × 8) block size. The feature vector of the image can be generated by combining all histogram of each block. Figure 12 shows the process of our LBP technique.

Algorithm 1 describes the LBP step by step.

Algorithm 1. *Feature Extraction using LBP*

1. **Input**: Palmprint images ROI of CHVD and ED.
2. **Output**: CHVD+LBP Features, ED+LBP features
3. **Begin**
4. **For** each sample of CHVD and ED images **do**
5. Divided palmprint images to(8 × 8) overlap blocks
6. **For** each pixel in the blocks **do**
7. Compare pixel to all 8 neighbors
8. **IF** Center pixel > neighbors **then**
9. Replace the neighbors to **1**
10. **Else**
11. Replace the neighbors to **0**
12. **End**
13. Generate the binary code from all the neighbors and convert it to decimal
14. Apply histogram for all the cell (in which their neighbors grater of smaller to center pixel)
15. $FV_{CHVD+LBP} = \bigcup_{i=1}^{N} LBP_{hist(i)}\left(CHVD\_ROI\right)$
16. $FV_{ED+LBP} = \bigcup_{i=1}^{N} LBP_{hist(i)}(ED\_ROI)$
17. Store the $FV_{CHVD+LBP}$ and FV_{ED+LBP} as feature vector.
18. **End**
19. **End**

2.3 Matching Process

The matching was done by compared input image (Query or Test) with the template which stored in the database that taken at the time of enrollment and compute the degree of similarity or dissimilarity from two templates. To achieve the score we used Euclidean distance measure to compute the similarity or the difference between the templates, The Euclidean distance can be calculated by using Eq. (6).

$$d(Test_i, Temp_j) = \sqrt{\sum_{i\&j=1}^{N} (Test\_V_i - Template\_V_j)^2} \quad (6)$$

Where, N is the number of feature in $Test\_V_i$ and $Template\_V_j$.

Algorithm 2 describes the *Matching* step by step.

Algorithm 2. *Matching*

1. **Input:** Palmprint feature vector
2. **Output:** Score matrix, Threshold values.
3. **Begin:**
4. **For** each test feature of each Subject**do**
5. $Test\_FV_i$
6. **For** each template feature of each Subject**do**
7. $Template\_FV_j$

$$dist(Test_i, Temp_j) = \sqrt{\sum_{i\&j=1}^{n} (Test\_FV_i - Template\_FV_j)^2}$$

8. Score_matrix= $d\,(Test_i, Temp_j)$
9. **End**
10. T_0=Score_matrix;/* total threshold values of system
11. minta = min(min(T_0)); /* minimum score

```
12. maxta = max(max(T_0));          /* maximum score
13. β = 100;                        /* size of optimal threshold
                                       values
14. Δ = (maxta - minta) / β;
15. const = 1 : 1 : β;              /* threshold vector
16. End
17. Store score_matrix in database as math file for
    discussion purposed.
18. End
```

2.4 Decision

In the final steps of the study the decision was taken either "Accepted "or "Rejected "with the help of threshold value (T). In the case of "Accepted", the distance (score S) should be($S \leq T$)otherwise it means "Rejected".

3. Results and Discussion

This section divided into different subsections. In section 3.1 dataset details are covered. The evaluation matrix is addressing in section 3.2, the results of extracting ROI by CHVD with LBP feature extraction is discussed in section 3.3. The section 3.4 addresses the results of ROI by ED and feature extraction techniques by using also LBP. The experimental applied on the laptop Dell, Intel core i3, CPU 2.20 GHz with RAM 8.00GB on 64-bit operating system (windows 7) and by MATLAB software 2013a.

3.1 Database

The experiments were evaluated on Chinese Academy of Sciences' Institute of Automation (CASIA)[41,42] Multi-Spectral Database v1.0 palmprint database which has 8 bits gray level (JPEG file), image size (768 × 576). This database contains 7200 images for 100 subjects for both left and right hands. For evaluate the algorithm the 100 subjects were selected for left hand with ID 001–100 and each subjects has 6 samples each labeled 01–06 and the total dataset containing 1200 images. The experimental applied on the laptop Dell, Intel core i3, CPU 2.20 GHz with RAM 8.00GB on 64-bit operating system (windows 7). Figure 13 shows some samples taken from CASIA dataset and their ROI part.

3.2 Evaluation Matrix

To evaluate any biometric system related to specific application there are different parameters namely False Accepted Rate (FAR), False Rejected Rate (FRR) and Equal Error Rate (EER). These parameters should be achieved the lowest values to get the best performance of the system. The FAR is the ratio of imposter score exceeding the threshold values divided by all the imposter score generated by the system and calculated by Eq. (7).

$$FAR = \frac{\text{Impostor Score exceeding thershold}}{\text{All Impostor Score}} \times 100 \quad (7)$$

The FRR is the ratio of genuine score falling below the threshold value divided by all the genuine score generated by the system and calculated by Eq. (8).

$$FRR = \frac{\text{Genuine Scores falling below thershold}}{\text{All Genuine Scores}} \times 100 \quad (8)$$

The EER can be calculated according to the Eq. (9)

$$EER = \frac{FAR + FRR}{2} \quad (9)$$

In addition to the above parameters there is Genuine Accept Rate (GAR) which shows the relation between FAR and FRR with the help of threshold values. Also the Receiver Operating Characteristic (ROC) curves shows the FAR values which are changed related to GAR values and it shows the performance of the system. The GAR value is calculated by Eq. (10).

$$GAR = 1 - FRR \quad (10)$$

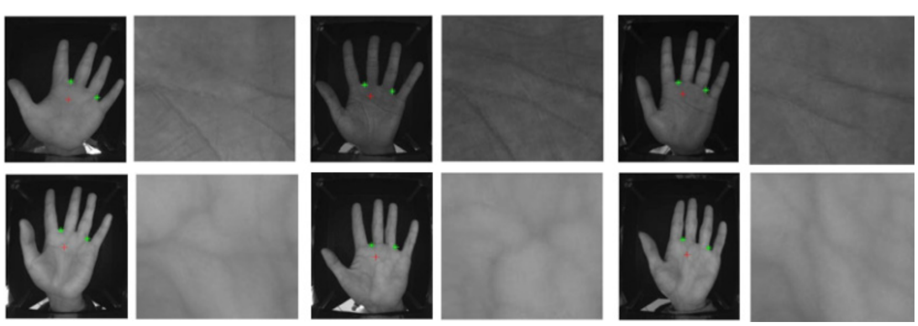


Figure 13. Samples taken from CASIA dataset with extract ROI.

3.3 Results of CHVD ROI with LBP

The performance of the system was evaluated by CHVD method with LBP feature extraction technique. The size of ROI was (155 × 155) which applied on dataset size of 100 users, each user has 6 samples. The threshold values were generated from the score matrix at the matching stages. There are 100 threshold values ranged from 0 to 1.

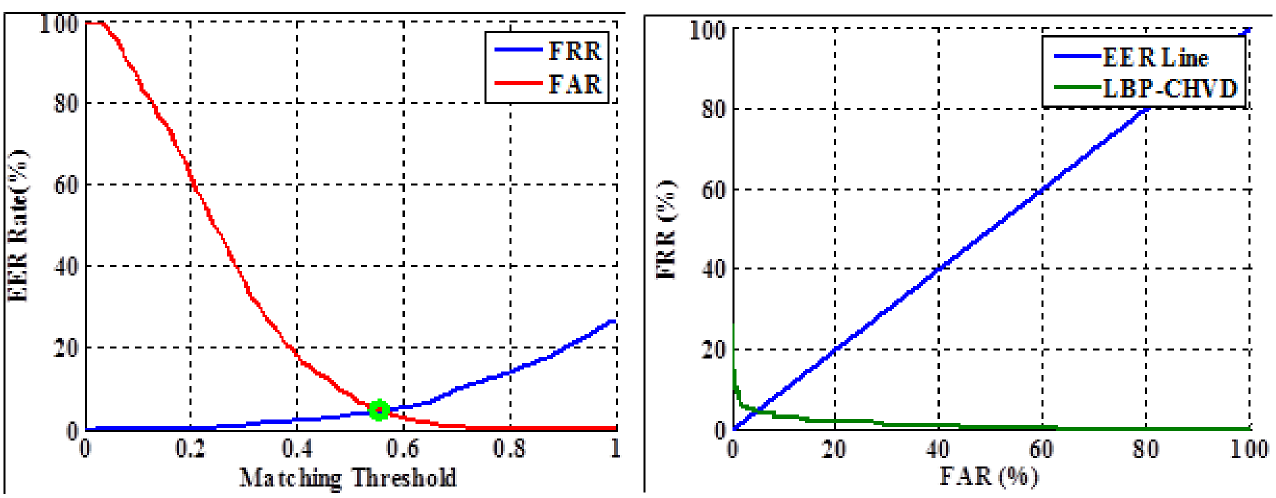
Table 1. Performance of the system based on CHVD with LBP Feature

CHVD + LBP				
T	**FAR (%)**	**FRR (%)**	**EER (%)**	**GAR (%)**
0	0	100	50	50
0.1	0.035714	86.18182	43.10877	56.89123
0.2	0.071429	62.44444	31.25794	68.74206
0.3	0.964286	36.26263	18.61346	81.38654
0.4	2.214286	17.83838	10.02633	89.97367
0.5	3.464286	8	5.732143	94.26786
0.6	**5.142857**	**2.646465**	**3.894661**	**96.10534**
0.7	9.428571	0.707071	5.067821	94.93218
0.8	13.42857	0.242424	6.835498	93.1645
0.9	19.39286	0.10101	9.746934	90.25307
1	26.60714	0.040404	13.32377	86.67623

The system can achieved the best performance with minimum EER and maximum GAR which determined with help of threshold values. The system achieved different results on different threshold values e.g. on T = 0 both EER and GAR of the system were 50% that means higher EER and minimum GAR of the system. The system achieved the best performance with minimum EER of 3.894661% and maximum GAR of 96.10534% at the threshold value of 0.6. Table 1 shows the results of the system by different T values with FAR, FRR, EER and GAR. Figure 14a depicts the relation between FAR and FRR with the help of threshold values and Figure 14b shows the ROC of the system by GAR Vs. FAR on different threshold values.

3.4 Results of ED with LBP

In the second experimental, the ED method was used to extract the ROI of (131 × 131) size then passed to LBP feature extraction method which evaluated by the same dataset applied in previous experiment. The system was achieved different results on different T values reached to 100and ranged from 0 to 1 which increased by 0.01 in each iteration and these threshold values were used to check the performance of the system. The efficiency result was achieved by minimum EER of



(a) (b)

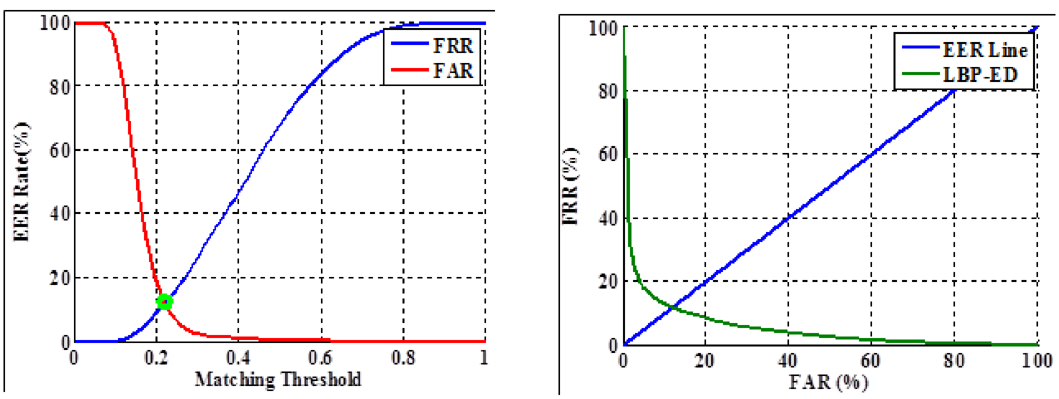
Figure 14. Performance of CHVD+LBP System: (a) Relation of FAR vs. FRR based on threshold value, and (b) ROC curve of system based on FAR vs. GAR.

11.76389% and Maximum GAR reached to 88.23611% which showed the best results compared with the previous technique. Table 2 shows the results of the system by different T values with FAR, FRR, EER and GAR and (Figure 15a) depicts the relation between FAR and FRR with help of threshold values and (Figure 15b) shows the ROC of the system by GARVs, FAR on different threshold values.

Finally, the comparison between both ROI methods shows that ED with LBP feature technique gave the least result with higher EER reached to 11.76389% and GAR of 88.23611% while CHVD with LBP achieved the best result with minimum EER of 3.894661% and maximum GAR of 96.10534%. Thecomparison between both methods based on EER and GAR is shown in (Figure 16a) and (Figure 16b) respectively.

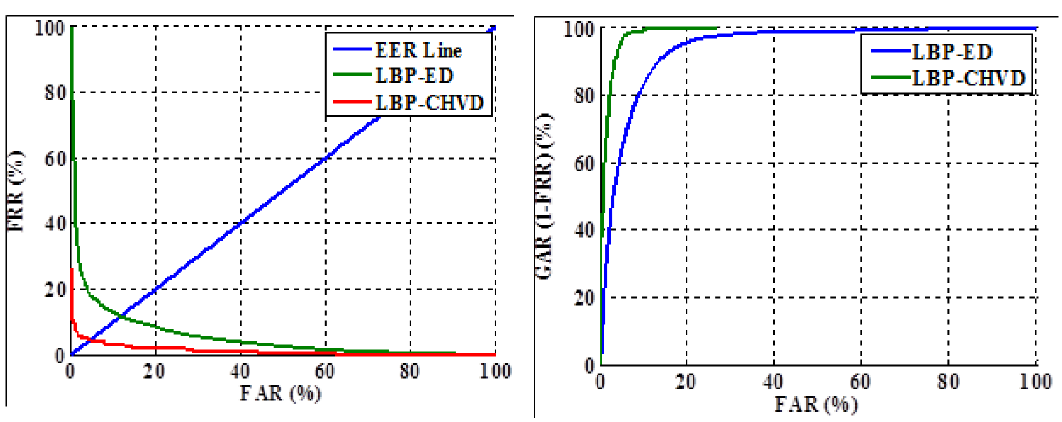
Table 2. Performance of the system based on ED with LBP feature

ED + LBP				
T	**FAR (%)**	**FRR (%)**	**EER (%)**	**GAR (%)**
0	0	100	50	50
0.1	0.178571	95.0101	47.59434	52.40566
0.2	9.25	18.0202	13.6351	86.3649
0.22	**11.75**	**11.77778**	**11.76389**	**88.23611**
0.3	26	2.383838	14.19192	85.80808
0.4	46.32143	1.111111	23.71627	76.28373
0.5	67.82143	0.666667	34.24405	65.75595
0.6	83.85714	0.363636	42.11039	57.88961
0.7	94.35714	0.20202	47.27958	52.72042
0.8	99	0.060606	49.5303	50.4697
0.9	99.96429	0	49.98214	50.01786
1	100	0	50	50



(a) (b)

Figure 15. Performance of ED+LBP: (a) Relation of FAR vs. FRR based on threshold value, and (b) ROC curve of FAR vs. GAR for.



(a) (b)

Figure 16. Comparison of GAR of CHVD and ED algorithm with LBP feature extraction: (a) EER curve, and (b) GAR Vs. FAR.

4. Conclusion

This research work evaluated the performance of two ROI techniques namely CHVD and ED on CASIA Multi-Spectral Database v1.0. The extraction of ROI is very important step in palmprint recognition system. It helps in extraction of features in terms of real part which contains rich information required for an authentication system. The research work evaluated ROI extracted by using CHVD and ED techniques, build feature matrix using LBP technique and PCA method which used for feature reduction. The LBP was applied for both ROIs and it was concluded from the experimental work that CHVD method achieved better performance with GAR reached to 96.10534% with EER equal to 3.894661%, while the EDROI method applied to LBP and PCA gave GAR reached to 88.23611% with EER equal to 11.76389%. This work may be extended to combine LBP with LPP features with neural network to achieve the best performance of the system.

5. References

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