International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 3 Issue 6, June - 2014

# Efficient Palmprint Recognition System

Vaibhav M. Rajput
Department of Electronics & Telecommunication Engineering,
Sinhgad College of Engineering,
Pune University, India

Prof. V. G. Raut
Department of Electronics & Telecommunication Engineering,
Sinhgad College of Engineering,
Pune University, India

***Abstract*— In the networked society there are a great number of systems that need biometric identification ,Biometrics is known to offer a reliable and natural solution for authentication purpose. Palmprint is one new Biometric which solves problems related to Automatic and Authentication recognition as compare to other Biometrics.It contains principle lines ,wrinkles and ridges on the surface of palm. These structure are stable and remain unchanged throughput life of an individual.. In this paper we have proposed palmprint recognition system. Palm is inner region between the hand wrist and the base of the fingers. Here, Local Binary Pattern (LBP) and its analysis are discussed for palm print recognitionwe also included Robust line orientation code (RLOC) for plamprint verification. This technique is simple, highly accurate and takes less time to process the palmprint image..**

***Keywords—Palmprint, Local Binary Pattern, Robust line orientation code Feature extraction, Chi-squared test, Pearson's correlation test;***

## I. INTRODUCTION

Now a days in information society, for personal verification and identification the biometrics is an important and effective solution. There are many security problems regarding access control of any system used to verify whether a person is true or not. Most of the available access control methods use Knowledge Based Identification System [1], which requires a user to enter a PIN or password for authentication. But, this technique has 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 behavioral or physiological characteristics to verify a person [2]. Behavioral characteristics are related to the behavior of a person like typing rhythm, gait and voice. On the other hand Physiological characteristics can be fingerprints, facial features, iris, hand geometry, DNA, palmprint and odour/scent. Selection of biometric depends upon various factors like universality, uniqueness, permanence, measurability, performance and acceptability of biometric [3].

Palm lies between the hand wrist and base of the fingers. It contains three flexion creases, secondary creases and lastly ridges. The flexion ridges also called as principle lines and secondary ridges called wrinkles. The ridge is important part. The flexion and wrinkles are formed between third, fourth and fifth months of pregnancy [3] and superficial lines appear after born. These depend on mostly genetic and most of the creases are not dependent. Even identical twins have different principle lines, wrinkles and ridges so due to this uniqueness and combining all three features we can make a system highly accurate in personal identification system.

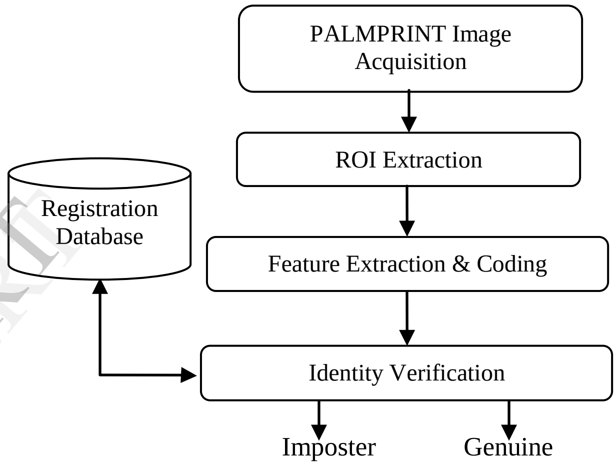


Figure 1: Schematic diagram for Palmprint recognition system [2]

In this paper, we are also investigating how to design a better orientation code for palmprint verification. Thus, we have included a novel scheme referred to as robust line orientation code (RLOC) has been proposed, which is regarded as an improved version of Competitive Code. In feature extraction stage, since Radon transform is a powerful tool to detect the directions of line feature, one of its variation named as the modified finite Radon transform (MFRAT) is proposed, which can extract the orientation feature of palmprint more accurately and solve its sub-sampling problem better. In matching stage, two strategies are adopted to improve the robustness of matching. The first one is that an enlarged training set is established to overcome large rotations problem caused by imperfect preprocessing. Another one is that a matching algorithm based on pixel-to-area comparison has been designed, which has better ability for slight translations, rotations and distortions.

Compared with other biometrics, palmprint recognition system have many advantages (1) low capturing device (2) low intrusiveness (3) stable line features (4) Minimal user acceptance (5) Accuracy (6) computational speed and (7) speed (8) low resolution imaging (9) rich texture feature. Palmprint is new biometrics in research area as compared to other biometrics, so there are many techniques which are still unexplored. A typical palmprint system contains five parts palmprint scanner device, preprocessing, feature extraction algorithm, matcher and database.

## II. LITERATURE REVIEW

David Zhang et al. [4, 6] propose approach employing Gabor filters to extract the phase information from a palmprint image. Tan *et al.* [1.8] given a minutiae based palmprint recognition system that can show unrestricted matching between the complete palmprint and misshapen palmprint, thus being able to identify the owner of the palmprint. Most researchers focus on palm lines as an important feature of palmprint image. Palm line includes principal lines and wrinkles, ridges but, principal lines get more attention because of their stable and highly distinctive and unique nature. These can easily be marked in all illumination conditions, compression and noise. Considering all these features Huang *et al.* [9] designed palmprint verification based on principal lines through feature extraction technique using modified finite radon transform.

Duta *et al.* [10] 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. Zhang *et al.* [11] devised a system which uses two level characteristics in palmprint verification; these are datum point variance and line feature matching. Wang *et al.* [12] 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 extracting to represent the palmprint features.

## 3. DATA ACQUISITION & PREPROCESSING

### *A. Data Acquisition*

Many researchers utilize four types of sensors CCD-based palmprint scanner devices, digital cameras, digital scanners and video cameras to collect palmprint images. Zang et al. And han [8,9] were the first two researchers formed teams for developing CCD-based palmprint scanners shown in Fig. 2.1,2.2, it captures high resolution and high quality palmprint images and align palms with them accurately because this device is pegs for helping for placement of hands which guides user. These devices show the development of various recognition algorithms because the images are captured in various controlled conditions of environment.

However, developing a CCD-based palmprint device requires a suitable selection of lens, camera, and light sources. Wong et al. Given some principles for CCD-based palmprint scanner device design [8]. These palmprint scanners also acquire high quality images and they are cheap in cost also as compared to other biometrics. In collection approaches based on digital scanners, digital scanners and video cameras requires less effort for system design as compared to CCD-based approach because they found in office environments also. They also not use peg shape approach for placement of hands, this approach is useful because in this method palmprint images are collected without contact and gives hygiene. It may cause problem as their quality of picture is low because they collect in uncontrolled conditions and various illuminations and distortion due to hand movements. Digital cameras are not useful for real time applications because of scanning time.

For our experiments we have used palmprint images form PolyU palmprint database five palmprint for each user and we have taken 15 different users. This gives us 75 samples. For matching 128 combinations pairs of the same user and 105 combination pairs of different users are taken. This gives us 233 pairs. We also used CASIO database in which total 5238 images are taken from 301 subjects from 602 objects.

### *B. Palmprint pre-processing*

In palmprint pre processing process we use 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. In this Palmprint image pre processing image 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 3.

Figure 2: The outlook of developed Palmprint acquisition device [10]


Figure 3: captured Palmprint sample

*1) Binarization:* Binarization converts a gray scale image into a binary image. There is a clear contrast between the background and hand images. Thus, a global thresholding can be applied to binarize the image.

*2) Boundary Tracing*: Boundary of the hand image is traced by using a boundary tracing algorithm on the binarize image as shown in Figure 4(3). We used Median filter algorithm, this algorithm traces the exterior boundaries of objects and returns row and column coordinates of each boundary pixel for each object, it also reduces noise and preserves boundary.It also reduces papper and salt noise in the image.

*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. We used sobel operator to compute the magnitude of palm lines. These magnitudes operates in all 4 directions both x and y directions to form histogram. After that we summed all 4 points and then take reference point and then we take roi box of 120*120 pixels to get clearer ROI so that we can get more principle lines and useful data.

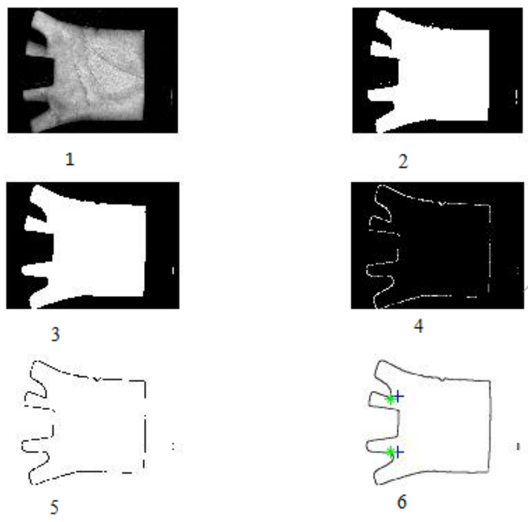


Figure 4: Palmprint image preprocessing 1. Input image 2. Binarized image 3. Traced boundary of binarized image 4. Extract reference points 5. Specified Region of interest 6. Region of interest

## 4. PROPOSED METHOD

*A. Analysis of Local Features*

In this we find palmprint image enhanced techniques are applied to make palm more clearly under all conditions. This technique also removes noise and thin lines in image. To perform this we use 2D smoothing filter, in this each pixel is replaced by average of pixel values in its 3*3 neighbourhood.

After that we find Feature extraction technique for palmprint image calculated using Local Binary Pattern as print image as followed:

1) Take enhanced palmprint image as input and compute LBP by specifying neighbor set and radius to form circular neighborhood.
2) Now take normalization operation to change the range of pixel intensity value and to achieve consistency among the dynamic range of intensity value.
3) Now generate LBP histogram
4) Store LBP values of histograms as a feature vector as shown in Fig. 4

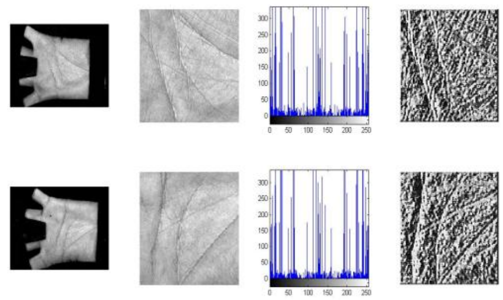

Figure 5: Feature extraction using Local Binary Pattern

For RLOC code we used other feature matching technique Called Modified radon transform which is improved version of Finite radon transform

$$r[Lk] = MFRAT\, f(k) = (i,j)\sum Lk\, f[i,j],$$

where Lk denotes the set of points that make up a line on the lattice $Z^2P$, which means

$$Lk = \{(i,j) : j = k(i - i0) + j0,\ I \in Zp\},$$

where $(i0, j0)$ denotes the center point of the lattice $Z^2P$ , and $k$ also means the corresponding slope of $Lk$. Compared with the FRAT, the MFRAT removes the intercept $l$ in $Lk,l$ . Consequently, for any given slope $k$, the summation of only one line, which passes through the center point $(i0, j0)$ of $Z^2P$ , is calculated. It should be pointed out that all lines at different directions have an identical number of pixels. Unlike the FRAT, the MFRAT is not an invertible transform, just designed for feature extraction MFRAT is more flexible for detecting the orientation of lines than FRAT. Because palm lines are negative lines, whose luminance is lower than that of background, we can calculate the direction of center point $f(i0, j0)$ of the lattice $Z^2P$ by using the MFRAT and winner-take-all rule:

$$Wk(i0,j0) = \arg(\min k(r[Lk])),\ k = 1, 2, \ldots, N,$$

where $Wk(i0,j0)$ is the winner index of orientation of center point $f(i0, j0)$.

In similar way, the directions of all pixels can be calculated if the center of lattice $Z^2P$ moves over an image pixel-by-pixel. For an image $I(x, y)$ of size $m \times n$, if all pixels are replaced by their winner index of direction, a new image, i.e., the orientation map is created, which is the feature image.

$$original\ map = \begin{bmatrix} w(1,1) & \cdots & w(1,n) \\ \vdots & \ddots & \vdots \\ w(m,1) & \cdots & w(m,n) \end{bmatrix}$$

Here $w_{(x,y)}$ means the winner index of orientation of pixel I(x,y).

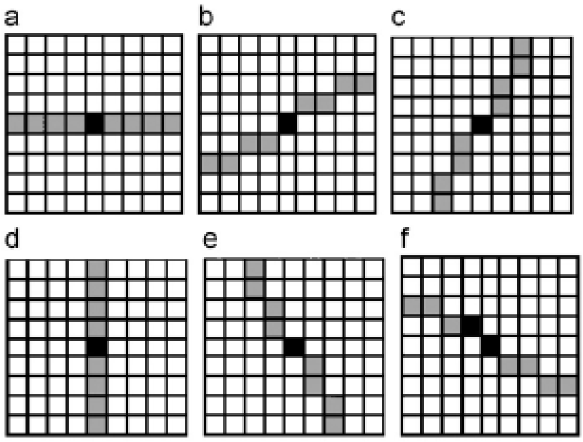


Figure 6: The 9*9 MFRAT at the directions $0^0, 30^0, 60^0, 90^0, 120^0, 150^0$ and $L_k$ is 1 pixel wide

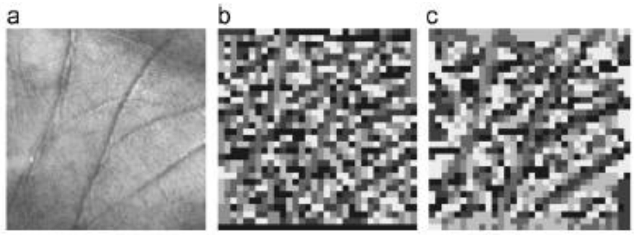


Figure 7:Comparison between Competitive code and RLOC (a) original image (b)Competitive code (c) RLOC

We used Chi-square test and Pearson correlation test for feature matching purpose in LBP and in RLOC we used pixel to small square area for matching purpose.

1) Chi-square test: It used to measure the whether two different histograms are similar or not, so that we can measure the dissimilarity between given image and reference image sets. It is calculated using formula:

$$x(X^{P,}, X^{G}) = \sum_{i=0}^{l} \frac{(H_i^P - H_i^G)^2}{H_i^P + H_i^G}$$

Where, *P* represents the observed histogram data (input captured 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: It is used for comparing images in many image processing applications like object recognition, image registration. It is also used to measure another similarity measure which evaluates the degree of correlation between the input histogram and reference histogram. Formula is given:

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

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 either using chi-square or pear son's correlation test.

3) Pixel to Small area comparison : In this method, we devise a matching algorithm based on pixel-to- Small area comparison to improve the robustness of matching.

Suppose that *A* and *B* are two feature images, and they come from same palm but are captured in different time intervals. In addition, the size of *A* and *B* is $m \times n$. Moreover, suppose that *A(i, j )* and *B(x, y)* are two corresponding points in same position. Hence, if there are no translations and rotations between them, at this time we know "$i = x$" and "$j = y$". However, due to the effect of translations, rotations or distortions *A(i, j )* and *B(x, y)* do not always appear in same position (we call it as false position problem). Further speaking, there is a very large probability that *B(x, y)* appears in a small area around *B(i, j)*. Under this analysis, the matching score from *A* to *B* is defined as follows:

$$s(A,B) = \frac{(\sum_{i=1}^{m}\sum_{j=1}^{n} A(i,j)\ U\ B(i,j)}{m \times n}$$

where "∪" is the logical "EQUAL" operation, which means that the value of *A(i, j )* ∪ . *B(i, j)* will be 1 if *A(i, j )* and at least one point of . *B(i, j)* are equal, otherwise it will be 0. Particularly, . *B(i, j)* can be defined as different shapes. For example, Fig. 8 shows pixel-to-area comparison In Figs. 5(b) and (c), . *B(i, j)* is defined small square (*B(i−1,j−1), B(i −* 1, *j* + 1*), B(i −* 1*,j), B(i +* 1*, j), B(i, j),B(i, j −* 1*), B(i, j +*1*), B(i +*1*, j +*1*), B(i +*1*, j −*1*)*) area, respectively. Obviously, the pixel-to-area comparison has better fault tolerant ability. In similar way, the matching score from *B* to *A* can also be defined as

$$s(A,B) = \frac{(\sum_{i=1}^{m}\sum_{j=1}^{n} B(i,j)\ U\ \bar{A}(i,j)}{m \times n}$$

At last, the matching score between *A* and *B* is defined as

*S(A,B)* = *S(B,A)* = Max(*s(A,B), s(B, A)).*

Theoretically speaking, *S(A,B)* is between 0 and 1, and the larger the matching score the greater the similarity between *A* and *B*. The matching score of a perfect match is 1.

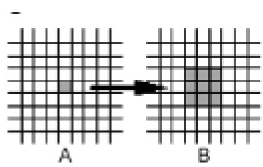


Figure 8: Pixel to small square area comparison

## 5. RESULTS & CONCLUSIONS

### *A. RESULT ANALYSIS*

The score of this proposed method is genuine and imposter data using Chi-square dissimilarity test and Pearson correlation similarity test are distributed along 2-D axes to clearly shows the discrimination among them. As shown in

Figure 6 depicts the corresponding false acceptance rate (FAR) and false rejection rate (FRR) curves at different threshold value.

$$\text{FRR} = \frac{\text{Total no of rejected genuiene claims}}{\text{Total no of genuiene acceses}}$$

$$\text{FAR} = \frac{\text{Total no of accepted imposter claims}}{\text{Total no of imposter acceses}}$$

FRR & FAR plot is shown in following figure.

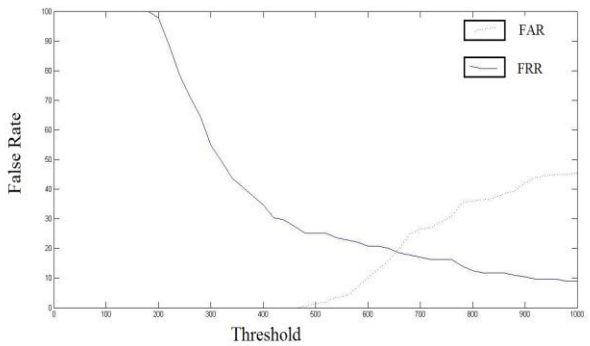


Figure 9: FAR and FRR curve of proposed system

*B PALM Database*

The database for PALM images is provided by PolyU University. The Polytechnic University database consists of five palmprint 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.

*C. Conclusions*

We chose LBP neighborhood of minimum window size 3 × 3. Region of Interest is extracted from image in the database. Median filter is used to remove noise as it also preserves edges. Sobel operator is employed to detect edges as we need only strong edges. Experimental analysis for variation in ROI selection shows that ROI sizes 120*120 are efficient for this database. By applying Sobel and Median filter, Pre-processing is completed.

TABLE I. Computation time for key processes

| [1] ***Operations*** | [2] ***Time (sec)*** |
|---|---|
| ROI extraction | [1] 2.379 |
| Feature extraction | [2] 0.7492 |
| Feature matching | [3] 0.266 |

Local Binary Pattern (LBP) are utilised for feature extraction. Table I gives time taken for key processes in the recognition system. Finally, we employed Chi-square and Pearson`s correlation tests to measure score of genuine and imposter data. The system achieves an accuracy of 99.37%

For RLOC In this paper, we proposed a robust line orientation code for palmprint verification, which has several obvious advantages. The first one is that the MFRAT can extract the orientation feature more accurately and solve the problem of sub-sampling better. The second one is that the use of an enlarged training set can overcome large rotations' problem well. Next, the designed pixel-to-area comparison has better fault tolerant ability The fourth advantage is that faster speed is obtained in feature extraction stage, which is three times faster than that of Competitive Code. Finally, the experimental results of verification show that the proposed approach can obtain 98.37% genuine acceptance rate, we have taken RLOC to compare with RLOC bt LBP hav better accuracy than RLOC.

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