Touch-Less Palm Print Biometric System.

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TOUCH-LESS PALM PRINT BIOMETRIC SYSTEM

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Abstract: In this research, we propose an innovative touch-less palm print recognition system. This project is motivated by the public's demand for non-invasive and hygienic biometric technology. For various reasons, users are concerned about touching the biometric scanners. Therefore, we propose to use a low-resolution web camera to capture the user's hand at a distance for recognition. The users do not need to touch any device for their palm print to be extracted for analysis. A novel hand tracking and palm print region of interest (ROI) extraction technique are used to track and capture the user's palm in real time video streams. The discriminative palm print features are extracted based on a new way that applies local binary pattern (LBP) texture descriptor on the palm print directional gradient responses. Experiments show promising result by using the proposed method. Performance can be further improved when a modified probabilistic neural network (PNN) is used for feature matching.

1 INTRODUCTION

Palm print recognition is a biometric technology which recognizes a person based on his/her palm print pattern. Palm print serves as a reliable human identifier because the print patterns are not duplicated in other people, even in monozygotic twins. More importantly, the details of these ridges are permanent. The ridge structures are formed at about thirteenth weeks of the human embryonic development and are completed by about eighteenth week (C. Harold and M. Charles, 1943). The formation remains unchanged from that time on throughout life except for size. After death, decomposition of the skin is last to occur in the area of the palm print. Compared with the other physical biometric characteristics, palm print authentication has several advantages: low-resolution imaging, low-intrusiveness, stable line features and low-cost capturing device.

Currently, most of the palm print biometrics utilize scanner or CCD camera as the input sensor. The users must touch the sensor for their hand images to be acquired. In public areas, like the hospital especially, the sanitary issue is of utmost importance. People are concerned about placing their fingers or hands on the same sensor where countless others have also placed theirs. This problem is particularly exacerbated in some Asian countries at the height of the SARS epidemic. Besides, latent palm prints which remain on the surface could be copied for illegitimate uses. Apart from that, the surface will get contaminated easily if not used right, especially in harsh, dirty, and outdoor environments. In addition, some conservative nations may resist placing their hands after a user of the opposite sex has touched the sensor. Therefore, there is pressing need for a biometric technology which is flexible enough to capture the users' hand images without having the users to touch the platform of the sensor.

1.1 Related Work

A number of palm print recognition research have been reported in the literature and most of them address the efficiency of the feature extraction algorithms. The proposed palm print representation schemes include Eigenpalms (C. Harold and M. Charles, 1943), Fisherpalms (X. Wu et al., 2003), Gabor code (D. Zhang et al., 2003), Competitive Code (W. K. Kong and D. Zhang, 2004), Ordinal feature (Z. Sun et al., 2005), line features (J. Funada et al., 1998), and feature points (D. Zhang and W. Shu, 1999). However, not much detail of the palm print acquisition method was provided although the acquisition process is one of the key considerations in developing a fast and robust online recognition system. In earlier study, inked-based palm print images (J. Funada et al., 1998) (D. Zhang and W. Shu, 1999) were used. The palm prints were inked to paper and digitized using scanner. The two-step process was slow and is not suitable for online system. Recently, various input sensor technology like flatbed scanner, CCD camera, CMOS camera, and infrared sensor have been introduced for more straight-forward palm print acquisition. Among the technology, scanner and CCD camera are the commonly used input devices (C. Harold and M. Charles, 1943) (X. Wu et al., 2003). Scanner and CCD camera are able to provide very high quality images with little loss of information. However, the process of scanning a palm image requires some time (a few seconds) and the delay cannot cope with the requirement of an online system. Zhang et al. (D. Zhang et al., 2003) proposed the use of CCD camera in semi-closed environment for online palm print acquisition and good results had been reported by using this approach. In this paper, we explore the use of a low-resolution web-cam for palm print acquisition and recognition in real-time system.

1.2 Challenges

There is high demand for touch-less biometrics due to various social and sanitary issues. However, the design of touch-less palm print system is not easy. Since the touch-less system does not restrict the user to touch or hold any platform and guidance peg, the system must be able to detect the existence of hand once the hand is presented on the input sensor. The main challenges in designing the touch-less system are highlighted as follow:

- **Distance between the hand and input sensor** – Since the user's hand is not touching any platform, the distance of the hand from the input sensor may vary. If the hand is placed too far away from the input sensor, the palm print details will be lost. On the other hand, if the hand is positioned too near to the input sensor, the sensor may not be able to capture the entire hand image and some area of the palm print maybe missing. Thus, a system which allows flexible range of distance between the hand and the input sensor should be designed.
- **Clenched fingers/palm** – Some users may overly clench their fingers and palm due to nervousness or other factors. If the user's fingers and palm are hold tightly together, the skin surface of the palm tends to crumple and fold up and produce some non-permanent wrinkles that may perturb the performance of system. Therefore, a robust algorithm that could tackle this situation must be devised.
- **Hand position and rotation** – As no guidance peg is used to constraint the user's hand, the user may place his/her hand in various directions and position. The system must be able to cope with changes in position and orientation of the user's hand in a less restrictive environment.
- **Lighting illumination** - Variation in lighting can have significant effect on the ability of the system to recognize individuals. Thus, the system must be capable of generalizing the palm print images across lighting changes.

1.3 Contributions

In this paper, we have endeavoured to develop an online touch-less palm print recognition system that attempts to confront the challenges above. A touch-less palm print recognition system is designed by using low-resolution CMOS web camera to acquire real-time palm print images. A novel hand tracking algorithm is developed to automatically track and detect the region of interest (ROI) of the palm print. A pre-processing step is proposed to correct the illumination and orientation in the image. As edges (principal lines, wrinkles and ridges) capture the most important aspects of the palm print images, an algorithm is developed to preserve and enhance the line structures under varying illumination and pose changes. We have proposed a new feature extraction method to extract the distinguishing palm print feature for representation. Gradient operator is applied to obtain the directional responses of the palm print and LBP is used to obtain the texture description of the palm pattern in different directions. Besides, a modified PNN is also devised as the real-time feature matching tool in this research.

2 PROPOSED SYSTEM

In this paper, we propose a touch-less online palm print recognition system. We describe a flexible hand tracking and ROI locator to detect and extract the palm print in real-time video stream. The algorithm works under typical office lighting and daylight conditions. Figure 1 shows the framework of the proposed system.

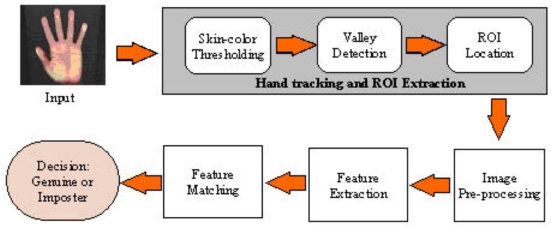


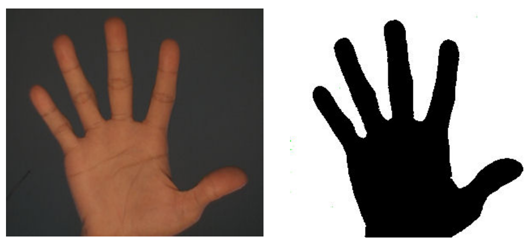
Figure 1: The proposed touch-less palm print recognition system.

2.1 Hand Tracking and ROI Extraction

The hand tracking and ROI extraction step consists of three stages. First, we segment the hand image from the background by using the skin-colour thresholding method. After that, a valley detection algorithm is used to find the valleys of the fingers. These valleys serve as the base points to locate the palm print region. The details of the steps are provided in the following sections.

2.1.1 Skin-Colour Thresholding

In order to segment human hand from the background, the skin colour modal proposed by (internet: Face Detection, 2000) is used. The human skin colour can be modelled as a Gaussian distribution, $N(\mu,\sigma)$, in the chromatic colour space, x. The chromatic colour space can remove luminance from the colour representation. To segment the hand from the background, the likelihood of the skin colour, L, can be computed by as $L=\exp\left[-0.5(x-\mu)^{T}\sigma^{-1}(x-\mu)\right]$ where μ and σ are the mean and covariance of the skin colour distribution. We use samples from 1005 skin colour images to determine the values of μ and σ. After the skin likelihood value is determined, the hand is segmented from the background by using the thresholding method. Figure 2 depicts the result of binarizing a hand image.

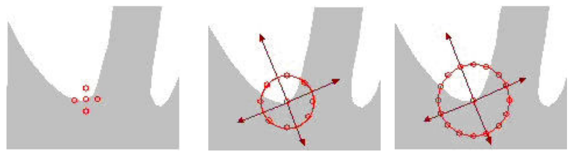


(a) (b)

Figure 2: Skin-colour thresholding: (a) The original hand image; (b) segmented hand image in binary form.

2.1.2 Valley Detection

We propose a novel competitive hand valley detection (CHVD) algorithm to locate the ROI of the palm. We trace along the contour of the hand to find possible valley locations. A pixel is considered a valley if it has some neighboring points lying in the non-hand region while the majority neighboring points are in the hand region (Figure 3). If a line is directed outwards from the pixel, the line must not cross any hand region along the way. Based on these assumptions, four conditions are formulated to test the existence of a valley. A pixel must satisfy all the four conditions to be qualified as a valley location. If it fails one the conditions, the pixel will be disregarded and the algorithm proceeds to check for valley-existence in the next pixel. Rather than scanning the entire hand image for valley location, the competitive valley checking method greatly speeds up the valley detection process.



(a) (b) (c)

Figure 3: The proposed competitive hand valley detection algorithm.

The four conditions to check the current pixel for valley existence are:

- **Condition 1:** Four checking-points with equal distance are placed around the current pixel (Figure 3(a)). The four points are placed β pixels away from the current pixel. If one of the points falls in the non-hand region (pixel value = 1), while the remaining within the hand region (pixel values = 0), this pixel is considered a candidate for valley and we proceed to check for Condition 2. Otherwise, the test stops and the algorithm proceeds to check the next pixel.
- **Condition 2:** The distance of the checking-points from the current pixel is increased to $\beta+\alpha$ pixels, and the number of checking-points is increased to eight (Figure 3(b)). If there is at least 1 and not more than 4 consecutive neighbouring points falling in the non-hand region, while the remaining within the hand region, this pixel satisfies the second condition and we proceed to the next condition.
- **Condition 3:** The number of checking-points is increased to 16. The distance of the points from the current pixel is $\beta+\alpha+\mu$ pixels. If there is at least 1 and not more than 7 points falling in the

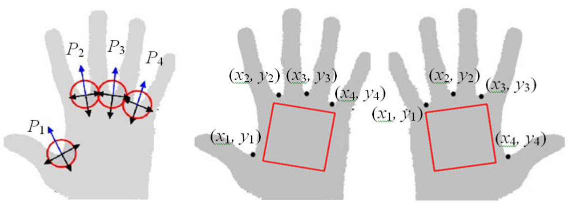
non-hand region, while the remaining points within the hand region, this pixel is considered a candidate for valley and we proceed to the last condition.

- **Condition 4:** To complete the test, a line is drawn from the current pixel towards the non-hand region (Figure 3(b)). This is to avoid erroneous detection of a gap /loop-hole in the hand as valley. If this line does not pass through any hand-region along the way, the current pixel is asserted as a valley point.

In this research, the values of β, α, and μ are set to 10. We set the range of the number of checking-points in the non-hand region in the three conditions to be 1, 1 $\leq$points< 4, and 1 $\leq$points< 7, respectively. This is based on the assumption that nobody can stretch his/her finger apart beyond 120^o. For example, the angle between the 2 fingers illustrated in Figure 3(c) is approximately 90^o estimated based on the sectors of the circle between the fingers (each sector = 22.5^o).

2.1.3 ROI Location

After obtaining the valleys of the finger, P_1, P_2, P_3, and P_4, a line is formed between P_2 and P_4. After that, a square is drawn below the line as shown in Figure 4(b). The square represents the region of interest (ROI) of the palm. Based on the experiment, the average time taken to detect and locate the ROI is less than 1 millisecond.



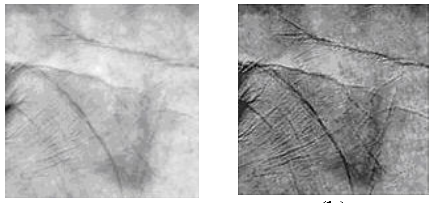
(a) (b) (c)

Figure 4: The ROI location technique: (a) Locations of the 4 valleys, (b) a line is drawn to connect P_2 and P_4. A square is drawn from the line. This square forms the ROI of the palm, (c) the ROI detected in the other side of the hand.

2.2 Image Pre-processing

As the ROIs are of different sizes and orientations, the pre-processing job is performed to align all the ROIs into the same locations. First, the images are rotated to the right-angle position by using the *Y*-axis as the rotation-reference axis. After that, as the size of the ROIs vary from hand to hand (depending on the sizes of the palms), they are resized to a standard image size by using *bicubic* interpolation. In this research, the images are resized to 150 x 150 pixels.

We enhance the contrast and sharpness of the palm print images so that the dominant palm print features like principal lines and ridges can be highlighted and become disguisable from the skin surface. The Laplacian isotropic derivative operator is used for this purpose. After that, the Gaussian low-pass filter is applied to smooth the palm print images and bridge some small gaps in the lines. Figure 5(a) shows the original palm print image and Figure 5(b) depicts the result of applying the image enhancement operators. The detail in the enhanced image is clearer and sharper in which fine details like the ridges are more visible now.



(a) (b)

Figure 5: (a) The original palm print, (b) palm print after the contrast adjustment and smoothing effect.

2.3 Feature Extraction

We propose a new way to apply the Local Binary Patterns (LBP) texture descriptor (T. Ojala et al., 2002) on the directional responses of gradient operator. Unlike fingerprint which flows in uniform structure with alternating ridges and furrows, the texture of palm print is irregular and the lines and ridges can flow in various directions. This motivates us to decompose the line patterns into four directions and study them separately. LBP is then used to analyze and describe the texture of the palm print in the various directions.

The Sobel operator is deployed in this work to obtain the palm print responses in different orientations. The Sobel operator is a well-known filter that can be used to detect discrete directional gradient. We applied Sobel operator to find palm print responses along the horizontal, vertical and diagonal in minus and plus 45 degree directions. The Sobel masks used are illustrated in Figure 6.

-1	-2	-1	-1	0	1	0	1	2	-2	-1	0
0	0	0	-2	0	2	-1	0	1	-1	0	1
1	2	1	-1	0	1	-2	-1	0	0	1	2
	(a)			(b)			(c)			(d)	

Figure 6: The Sobel masks used to detect the palm print (a) horizontally, (b) vertically, (c) diagonally at positive 45^o, and (d) diagonally at negative 45^o.

For computational efficiency and noise reduction purposes, we first decompose the palm print image into lower resolution images by using wavelet transformation before applying the Sobel operator. Refer (T. Connie et al., 2005) for the detail of applying wavelet transformation on palm print images. Figure 7 shows the components of the palm print in four directions by applying Sobel operator.

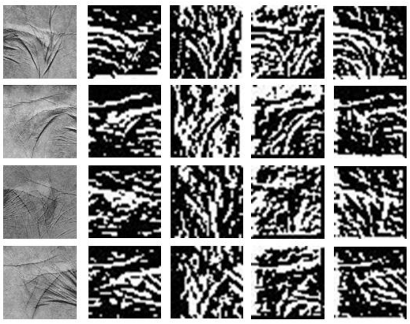


Figure 7: Examples of directional responses derived using Sobel operator. (a) Original palm print images, (b) to (e) components of the images in the horizontal, vertical, positive 45^o, and negative 45^o directions.

2.3.1 Local Binary Patterns

The LBP operator (T. Ojala et al., 2002) is a simple yet powerful texture descriptor that has been used in various applications. Its high discrimination ability and simplicity in computation have made it very suitable for online recognition system. LBP operator labels every pixel in an image by thresholding its neighboring pixels with the center value. Figure 8 illustrates an example how the binary label for a pixel value is obtained.

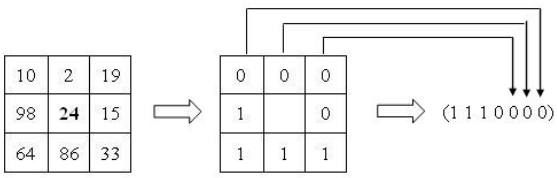


Figure 8: Example to calculate the binary label in LBP.

It is found that certain fundamental patterns in the bit string account for most of the information in the texture [15]. These fundamental patterns are termed as "uniform" patterns and they are bit strings with at most 2 bitwise transitions from 0 to 1 and vice versa. Examples of uniform patterns include 00000000, 11110000, and 00001100. A label is given to each of the uniform patterns and the other "non-uniform" patterns are assigned to a single label. After the labels have been determined, a histogram of the labels is constructed as:

$$H_l = \sum_{i,j} \{ L(i,j) = l \},\ l = 0,...n-1 \tag{1}$$

where n is the number of different labels produced by the LBP operator. The histograms of the labels are used as the texture descriptor. It contains information about the local descriptions in the image.

In this work, we divide the palm print images into several local regions, $R_1, R_2, ..., R_m$, and extract the texture descriptor from each region independently. The local texture descriptors are then concatenated to form a global descriptor of the image. We subdivide the image into 9 equally-sized sub-windows, and an overlapping window in the centre (Figure 9). The reason we form a window in the centre is because we believe that the region encodes important information of edge flow of the three principal lines. The same operation is performed on the other palm print components in the three other directions. Therefore, the texture descriptor for a given palm print will have a size of n (the number of labels) x m (the number of sub-windows) x 4 (the components of palm print in 4 directions).

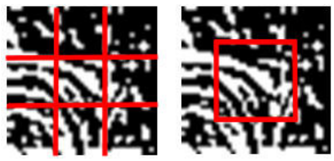


Figure 9: A palm print image is divided into rectangular sub-windows. (We show the sub-windows in two separate images for clearer illustration).

2.3.2 Feature Matching

In this research, the Chi-square measure is deployed as the feature matching tool:

$$\chi^2(P,G) = \sum_{i=0}^{n} \frac{(P_i - G_i)^2}{P_i + G_i} \tag{2}$$

where n is the number of length of the feature descriptor, P is the probe set, and G denotes the gallery set. We have also deployed a modified Probabilistic neural network (PNN) to classify the palm print texture descriptors using the neural networks approach. The motivations of using PNN are driven by its good generalization property and its ability to classify dataset in just one training epoch.

PNN is a kind of radial basis network primarily based on the Bayes-Parzen classification. Besides the input layer, it contains a pattern, summation and output layers (T. Andrew et al., 2006). The pattern layer consists of one neuron for each input vector in the training set, while the summation layer contains one neuron for each class to be recognized. The output layer merely holds the maximum value of the summation neurons to yield the final outcome (probability score). To tailor the specific requirement of the proposed online palm print recognition system, the formula to calculate the outcome of the pattern layer is modified to $out_j = \exp\left(-\sum_{i=1}^{n}((\boldsymbol{P}_i - \omega_{ij})^2 / (\boldsymbol{P}_i + \omega_{ij})) / \sigma\right)$. In this case, out_j is the output of neuron j in pattern layer; $\boldsymbol{P}_i$ refers to the probe set of user i, ω_{ij} denotes the weight between i^{th} neuron of the input layer and j^{th} neuron in the pattern layer. σ is the smoothing parameter of the Gaussian kernel and is also the only parameter dependent on the user's choice. In this paper, the value of σ is set to 0.1 (T. Andrew et al., 2006).

3 EXPERIMENT SETUP

In this experiment, a standard PC with Intel Pentium 4 HT processor (3.4 GHz) and 1024 MB random access memories is used. Our capturing device is a 1.3 mega pixel web camera. The palm print is detected in real-time video sequence at 25 fps. The image resolution is 640 x 480 pixels, with color output type in 256 RGB (8 bits-per-channel). The interval between capturing the next ROI is 2 seconds. The exposure parameter of the web-cam is set to low to reduce the effect of background light as the background light may disrupt the quality of the palm print image. We place a 9 watt warm-white light bulb beside the camera. The bulb emits yellowish light source that enhances the lines and ridges of the palm. A black cardboard is placed around the web-cam and light bulb to set up a semi-controlled environment as shown in Figure 10. The black cardboard can absorb some reflectance from the light bulb so that the palm image will not appear too bright.

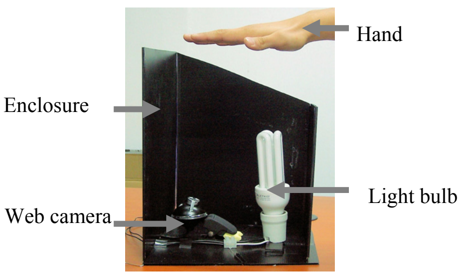


Figure 10: The experiment setup.

The proposed methodology is tested on a database containing palm images from 320 individuals. 147 of them are females, 236 of them are less than 30 years old, and 15 of them are more than 50 years old. The testing subjects come from different ethnic groups: 136 Chinese, followed by 125 Malays, 45 Indians, 6 Arabians, 2 Indonesians, 2 Pakistanis, a Africans, a Mongolian, a Sudanese and a Punjabi. Most of them are students and lecturers from Multimedia University. To investigate how well the system can identify unclear or worn palm prints due to laborious work, we have also invited ten cleaners to contribute their palm print images to our system.

The users can place their hands about 40cm to 60 cm above the input sensor. The users are requested to stretch their fingers during the image capturing process. They are allowed to wear rings and other ornaments. Besides, users with long finger nails can also be detected by the system. Twenty palm print images were captured from each hand and this yields a total of 12, 800 palm print images in the database.

4 RESULTS AND DISCUSSION

In this section, we conduct extensive experiments to evaluate the effectiveness and robustness of the proposed system. We first carried out palm print tracking in dynamic environment to validate the robustness of the proposed hand tracking technique. After that, we performed offline testing to evaluate the performance of the proposed algorithm.

4.1 Online Palm Print Tracking

The first experiment is conducted in the semi-controlled environment shown in Figure 10. A user was asked to present his hand above the web-cam and slowly rotate his hand to the left and right directions. The user was also asked to move his hand closer and gradually away from the web-cam. Some tracking results of the palm print region are shown in Figure 11.

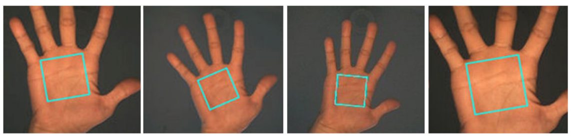


Figure 11: Some tracking results of the proposed palm print tracking algorithm in semi-controlled environment.

The proposed palm print tracking method performs quite well as the ROI of the palm print can be located regardless of changes in size and direction. The average time to track and locate the ROI is 12 milliseconds. We further assessed the effectiveness of the algorithm in dynamic environment. In this video sequence, the user had continuous body movements, and the image was disrupted by other background objects and varying illumination conditions. Figure 12 displays the test sequence to locate the palm print in dynamic environment.

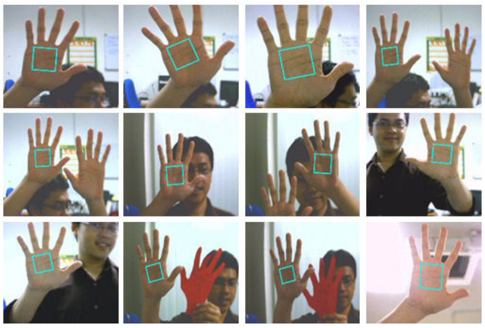


Figure 12: Some tracking result of the proposed palm print tracking algorithm in dynamic environment.

Based on the tracking result, the proposed algorithm performs well in dynamic environment. The images in the top row, for example, contain other background objects like calendar, whiteboard, computer and even the face of the user. The algorithm was able to locate the palm print region among the cluttered background. When both hands were present in the image (for example, the first image from the right in the first row), the algorithm detected one of the palm prints. We designed the system in such a way that only one hand is required to access the application. Therefore, the first palm detected in the video sequence was used for further analysis. Besides, we tried to spoof the algorithm by presenting a fake hand made from Manila paper. Some lines were drawn on the fake image to make it more "palm-like". Nevertheless, the algorithm still managed to recognize the real palm based on the colour cue. Apart from that, we wanted to investigate how well the tracking algorithm performs under adverse lighting condition. When the palm was placed under a bright light exposure (the first image from the right in the last row), the algorithm could locate the palm print region accurately.

4.2 Verification

The experiment was conducted based on the palm print images captured in the setting described in Section 3. Among the 20 images provided by each user for each hand, 10 images are used as gallery set while the others as probe set. Equal error rate (ERR) is used as the evaluation criteria in the experiment. EER is the average value of two error rates: false acceptance rate (FAR) and false rejection rate (FRR).

The proposed method is compared against other representative techniques in palm print recognition which include PCA (C. Harold and M. Charles, 1943), Competitive Code (W. K. Kong and D. Zhang, 2004) and Ordinal Code (Z. Sun et al., 2005). To differentiate our method from the others, we name it directional gradient based local binary pattern (DGLBP) thereafter. Figure 13 depicts the comparison among the four techniques. It is shown that DGLBP is comparable to that of Competitive Code and Ordinal Code. Apart from the promising result, DGLBP has a big advantage over the other methods because of its simplicity in computation. LBP operator only requires time complexity of $O(2^n)$, where n equals the number of neighbourhoods, to generate the labels once. Depending on the number of sub-regions formed in an image, the time complexity to produce the LBP descriptor is $O(mhw)$, where m denotes the number of sub-regions, while, h and w refer to the height and width of a sub-region, respectively. The complexity of the algorithm can be reduced to $O(mn)$ if the sizes of h and w are small.

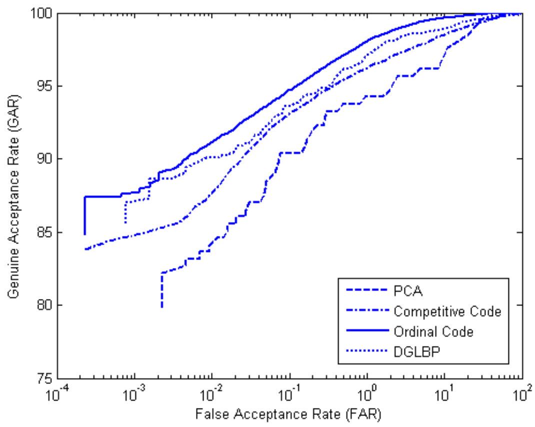


Figure 13: ROC which compares the performance of four palm print representative methods.

A comparative study was also conducted by using Chi-square measure and modified PNN. This is to investigate how well the modified PNN can improve the performance of the system. The comparison is provided in Table 1. Three training samples were used in training the modified PNN.

Table 1: The EER and the execution time taken for verification of each user.

Image Resolution	EER (%)	Average time (sec.)
Modified PNN	0.74	0.73
Chi-square measure	1.52	0.22

PNN had demonstrated superior performance as compared to Chi-square measure as PNN possesses better generalization property. However, the speed of training was achieved at the cost of increase in complexity and computational/ memory requirements. The time complexity for training by using PNN is $O(mp)$, where m denotes the input vector dimension and p is the number of training samples. The time recorded in Table 1 is the speed taken for PNN and Chi-square measure to run the verification test using 20 palm print samples. It can be observed that PNN indeed took longer time than Chi-square measure. However, the gain in performance is significant as the EER could be reduced from 1.52% to 0.74%. Therefore, PNN is still favoured over Chi-square measure in this research.

5 CONCLUSIONS

This paper presents an innovative touch-less palm print recognition. The proposed touch-less palm print recognition system offers several advantages like flexibility and user-friendliness. We proposed a novel palm print tracking algorithm to automatically detect and locate the ROI of the palm. The proposed algorithm works well under dynamic environment with cluttered background and varying illumination. A new feature extraction method has also been introduced to extract the palm print effectively. In addition, we applied a modified PNN to tailor the requirement of the online recognition system for palm print matching. Extensive experiments have been conducted to evaluate the performance of the system. Experiment results show that the proposed system is able to produce promising result. Apart from that, another valuable advantage is that the proposed system could perform very fast in real-time application. It takes less than 3 seconds to capture, process and verify a palm print image in a database containing 12, 800 images.

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