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# Automatic Personal Identification Using Feature Similarity Index Matching

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**Abstract: Problem statement:** Biometrics based personal identification is as an effective method for automatically recognizing, a person's identity with high confidence. Palmprint is an essential biometric feature for use in access control and forensic applications. In this study, we present a multi feature extraction, based on edge detection scheme, applying Log Gabor filter to enhance image structures and suppress noise. **Approach:** A novel Feature-Similarity Indexing (FSIM) of image algorithm is used to generate the matching score between the original image in database and the input test image. Feature Similarity (FSIM) index for full reference (image quality assurance) IQA is proposed based on the fact that Human Visual System (HVS) understands an image mainly according to its low-level features. **Results and Conclusion:** The experimental results achieve recognition accuracy using canny and perwitt FSIM of 97.3227 and 94.718%, respectively, on the publicly available database of Hong Kong Polytechnic University. Totally 500 images of 100 individuals, 4 samples for each palm are randomly selected to train in this research. Then we get every person each palm image as a template (total 100). Experimental evaluation using palmprint image databases clearly demonstrates the efficient recognition performance of the proposed algorithm compared with the conventional palmprint recognition algorithms.

**Key words:** Feature-Similarity Indexing (FSIM), Human Visual System (HVS) canny edge, log Gabor Phase congruency, gradient magnitude, palmprint recognition, palmprint recognition algorithms

## INTRODUCTION

Reliability in computer aided personal authentication is becoming increasingly important in the information-based world, for effective security system. Biometrics is a scientific discipline that involves methods of identifying people by their physical and or behavioral characteristics Basha *et al*. (2011); Birgale and Kokare (2010); Chan *et al*. (2010); Halawani and Albidewi (2010); Abandah and Anssari (2009) and Al-khouri and Bal (2007). Physiological characteristics of human beings are unique for every individual and are usually time invariant and easy to acquire. Palm print is one of the relatively new physiological biometrics due to its stable and unique characteristics. The rich information of palm print offers one of the powerful means in personal recognition.

A palm print contains distinctive features such as principal lines, wrinkles, ridges and valleys on the surface of the palm. Palmprint has abundant lines and ridge structure, which can be used for matching Cheng and Moon *et al*. (2008); Noh and Rhee (2005); Laadjel *et al*. (2008) and Sarhan (2009). The problem of palmprint-based personal identification can be described as follows: given an example palmprint, compare it with all of the possible candidates in the database to determine whether the queried example and the candidates are from the same palm. The search for the best matching is crucial for the performance of the system in terms of accuracy and efficiency. The criteria to measure the similarity for the search should be accurate and easy to calculate.

The remainder of this study is organized as follows. We present the edge detection techniques using canny and prewitt methods, followed by log Gabor filter. We introduce a Feature Similarity Index (FSIM) for full reference (image quality assurance) IQA is proposed based on the fact that Human Visual System (HVS) understands an image mainly according to its low-level features.

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## MATERIALS AND METHODS

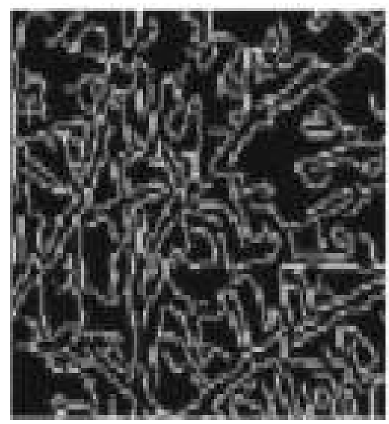
Edge detection is an essential process in image processing and many algorithms have been proposed. Some edge detection filters were developed with optimality (Canny, 1986). Canny evaluated the detectors by three criteria: good detection, good localization and low spurious response and he showed that the optimal detector for an isolated step edge should be the first derivative of Gaussian. The optimal canny edge detector for ramp edges was proposed by Petrou and Kittler (1991). Canny restricted the detector as a Finite Impulse Response (FIR) Filter. Sarkar and Boyer (1991) extended it to Infinite Impulse Response (IIR) filter. Besides the shape of the detector, another important problem is to set a proper detection scale. As suggested by Ekinci and Aykut (2007) multiple scales should be employed to describe the variety of the edge structures. Then these multi-scale ascriptions will be synthesized to form an edge map.

Canny used a fine-to-coarse feature synthesis strategy to mingle the multiscale edge information based on a set of predefined rules. Fields (1987) combined the multiscale edges in a coarse-to-fine tracking manner. The RRES (reasoning about edges in scale space) scheme of Jain *et al*. (1995) tends to be more complex with so many knowledge rules and continuous scale space. Considering that the synthesis of the multiscale edges is intricate, it itself an ill-posed problem Fig. 1 Shows the canny and prewitt edge detection of a palmprint image. It was found that canny edge detects more features than the prewitt.

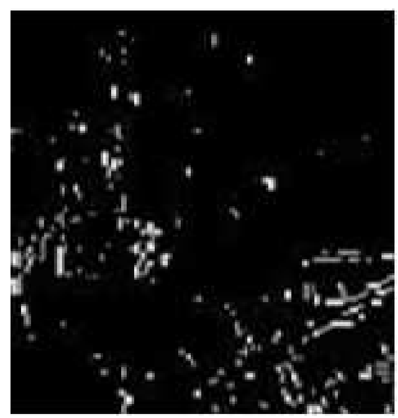
Gabor filters have invited lot of attention in biometrics research community, mainly due to its orientation selectivity, spatial localization and spatial-frequency characterization Wen and Zang (2007). An alternative to the Gabor filter is the log-Gabor filter proposed by Field. Fields (1987) Field proposes an alternate method to perform both the DC compensation and to overcome the bandwidth limitation of a traditional Gabor filter. The Log-Gabor filter has a response that is Gaussian when viewed on a logarithmic frequency scale instead of a linear one. This allows more information to be captured in the high frequency areas and also has desirable high pass characteristics.

Here, we present a multifeature extraction based on edge detection scheme. Applying Log Gabor Daugman (1988) and Kong *et al*. (2003) filters to every image and multiplies as a product function. Unlike many multiscale edge detectors, where the edge maps were formed at several scales and then synthesized together, our scheme determines edges as the local maxima in the product function, after the filtering. The filter multiplication enhances image structures and suppresses noise.

(a)



(b)



(c)

Fig. 1: (a) Test image (b) Canny Edge detection (c) Perwitt Edge Detection

An integrated edge map will be formed efficiently while avoiding the ill-posed edge synthesis process. It will be shown that much improvement is obtained on the localization accuracy and the detection results are better.

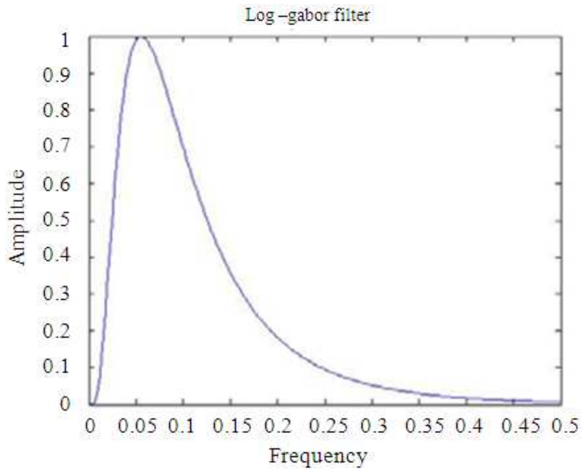



Fig. 2: Amplitude spectrum of a typical Log-Gabor filter on linear scale

**We adopt the log-Gabor filters because:** (1) One cannot construct Gabor filters of arbitrarily and width and still maintain a reasonably small DC component in the even-symmetric filter, while log-Gabor filters, by definition, have no DC component; and (2) The transfer function of the log-Gabor filter has an extended tail at the high frequency end, which makes it more capable to encode natural images than the ordinary.

The transfer function of a log-Gabor filter in the frequency domain is Eq. 1:

$$G(\omega) = \exp\left(\frac{-(\log\frac{\omega}{\omega_o})^2}{2\sigma_r^2}\right) \quad (1)$$

where, $\omega_0$ is the filter's center frequency and $\sigma_r$ controls the filter's bandwidth. Figure 2 shows the amplitude spectrum of a typical Log-Gabor filter on linear scale. Fig. 3 illustrates the Gabor filter responses of with low pass filter and palm image.

Feature Similarity Indexing maintains IQA (image quality assurance) based on the fact that Human Visual System (HVS) understands an image mainly according to its low-level features. The main feature of FSIM is phase congruency which is a dimensionless measure of the significance of a local structure Zhang *et al.* (2011) Due to phase congruency the contrast of the image will affect HVS but the secondary feature of FSIM which is the gradient magnitude control perception of image quality. Phase congruency and Gradient Magnitude play complementary roles in characterizing the image local quality and derive a single quality score.

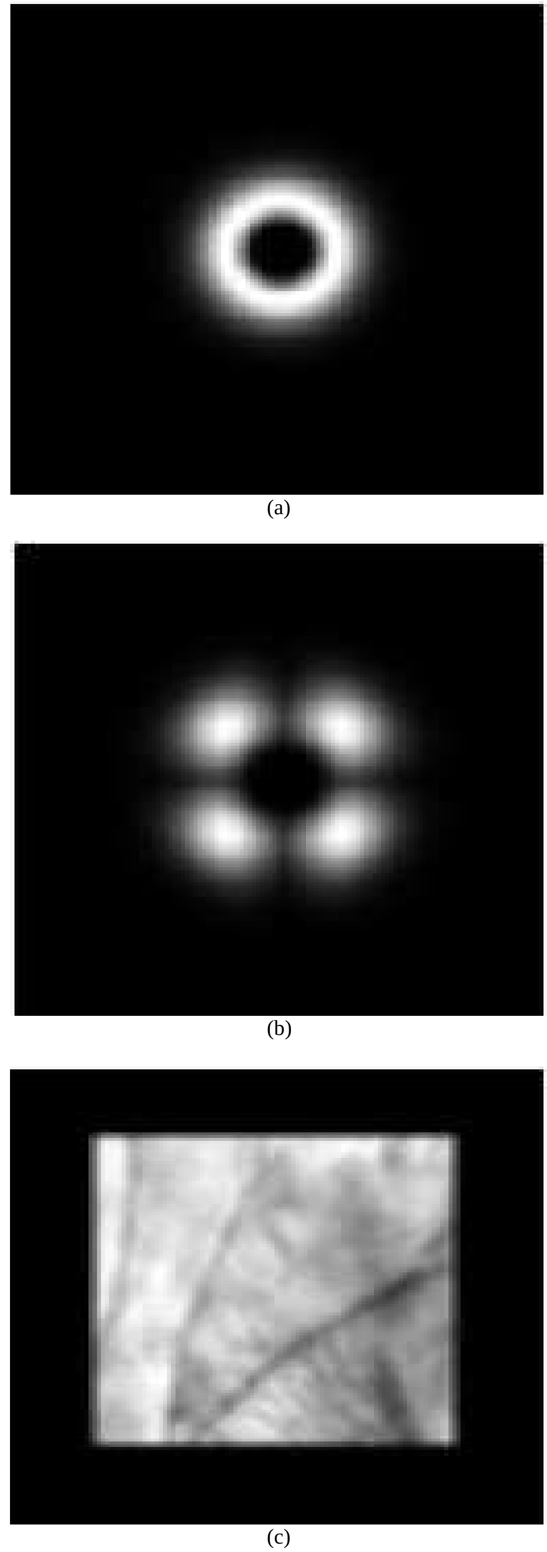
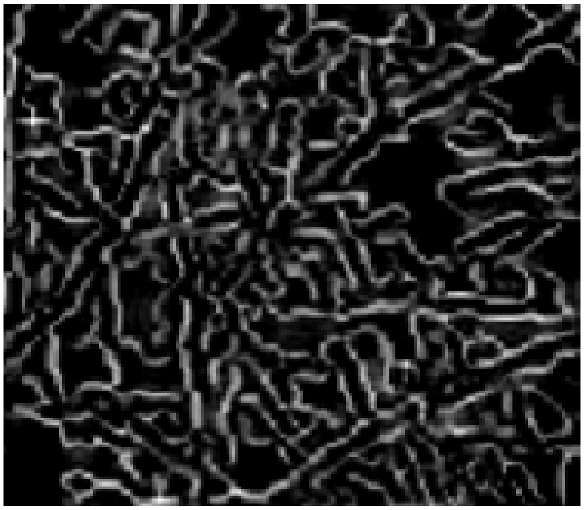
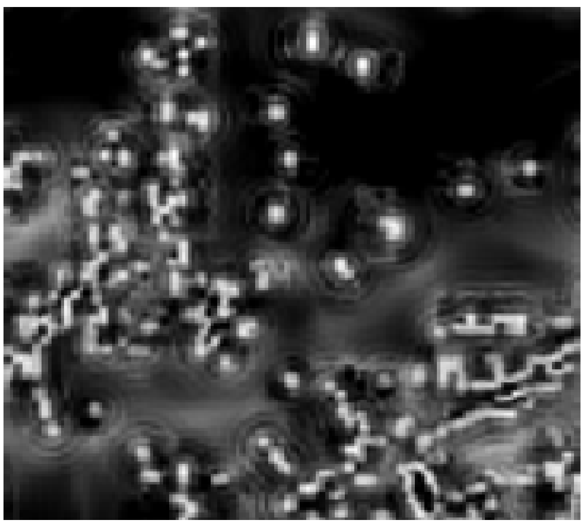



Fig. 3: (a) Log-Gabor Filter, (b) Log Gabor with Low pass-filter, (c) Log Gabor palm image



(a)



(b)

Fig. 4: Phase congruency of (a) canny image (b) prewitt image

Rather than assuming a feature is a point of maximal intensity gradient, the Local Energy Model postulates that features are perceived at points in an image where the Fourier components are maximally in phase.

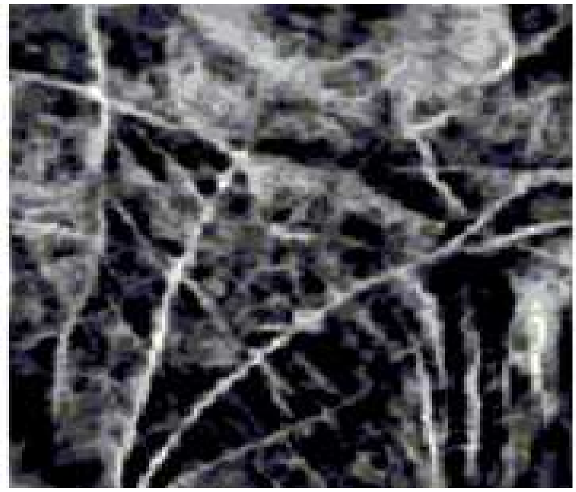
The 1D signal h(*x*) has odd symmetric and even symmetric filter scale denoted by $P_n^o$ and $P_n^e$ which form a quadrature pair.

The signal will form a response vector at position *x* on scale *n*:

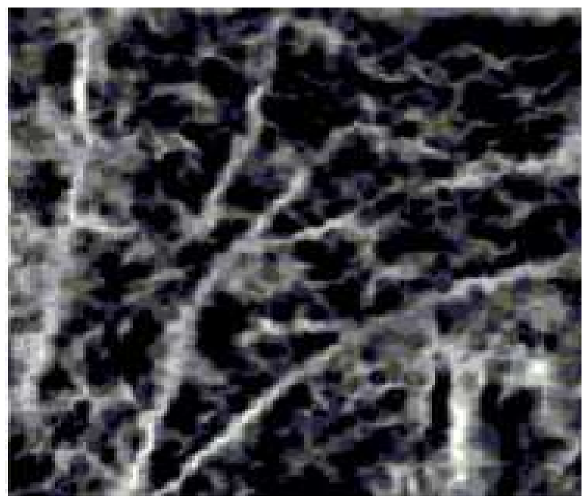
$$\left[E_n(x), O_n(x)\right] = \left[h(x) * P_n^o, h(x) * P_n^e\right] \tag{2}$$

The local amplitude on scale *n* is:

$$A_n(x) = \sqrt{E_n(x)^2 + O_n(x)^2}$$



(a)



(b)

Fig. 5: (a-b) Phase congruency of different palm images

Let $F(x) = \sum_n E_n(x)$ and:

$$H(x) = \sum_n O_n(x)$$

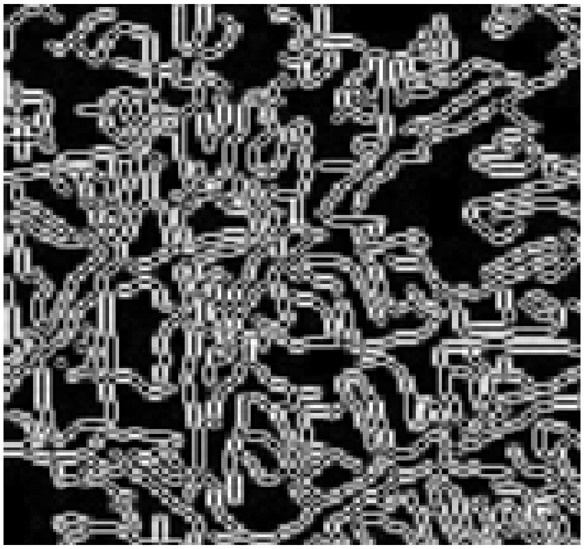
Then:

$$PC(x) = \frac{E(x)}{\in + \sum_n A_n(x)} \tag{3}$$

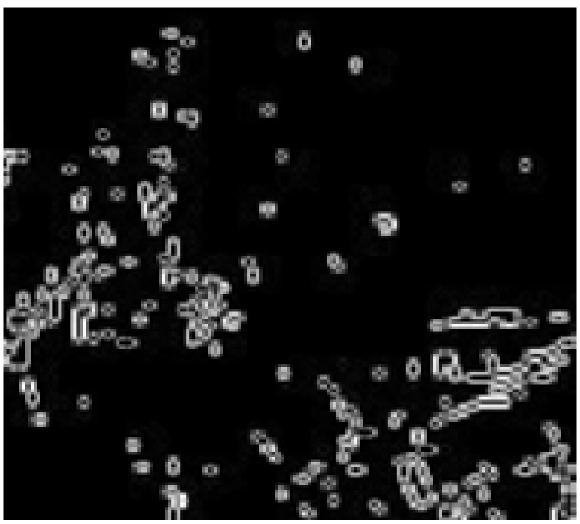
where, $E(x) = \sqrt{F^2(x) + H^2(x)}$

and ε is a small positive constant.

Figure 4 illustrates the Phase congruency of canny and perwit image. Figure 5 illustrates the Phase congruency maps extracted from the canny and perwitt palmprint image. And Fig. 6 explains the mapping of different palmprint images.



(a)



(b)

Fig. 6: Gradient Magnitude of (a) Canny (b) Perwitt

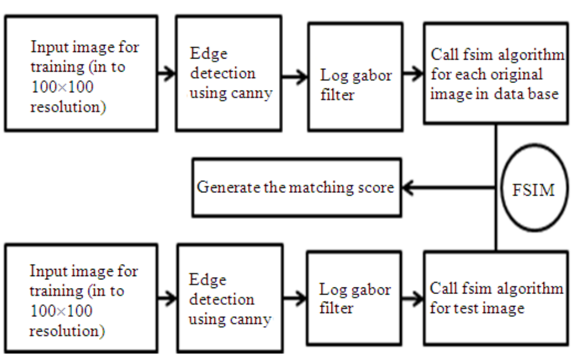



Fig. 7: The proposed FSIM based palmprint biometric verification model

Image gradient computation is a traditional topic in image processing. Gradient operators can be explained by convolution masks. Three commonly used gradient operators are the Sobel operator, the Prewitt operator Jain *et al*. (1995) and the Scharr-operator Jahne *et al*. (1999). Figure 6 illustrates the mapping of the gradient magnitude of canny and perwitt palmprint images respectively.

The partial derivatives $G_x(x)$ and $G_y(x)$ of the image, h(x) along horizontal and vertical directions, using the three gradient operators are used. The Gradient Magnitude (GM) of h(x) is then defined as:

$$G = \sqrt{G_x^2 + G_y^2} \quad (4)$$

Figure 7 shows overall framework of the proposed FSIM based palmprint biometric authentication. From Fig. 7, it can be seen that the images are given to canny edge detection to detect the edges. After the edges are detected, it is given to log Gabor filter to remove high frequency noise. We use FSIM algorithm to find the matching score between the test image and the original image sored in the database.

To present a novel Feature Similarity (FSIM) index for Image quality assurance we extract phase congruency and gradient magnitude feature maps. If we are going to calculate the similarity between images $h_1$ (test image) and $h_2$ (original image) denote it by $PC_1$ and $PC_2$. The PC maps are extracted from $h_1$ and $h_2$ and $G_1$ and $G_2$; the GM maps are extracted from them. For the analysis of color images, PC and GM features are extracted from their luminance channels. FSIM will be defined and computed based on $PC_1$, $PC_2$, $G_1$ and $G_2$. Furthermore, by incorporating the image chrominance information into FSIM, an IQA index for color images or gray scale image, denoted by FSIM*C*, will be obtained.

1st stage of the FSIM score is between $PC_1$ and $PC_2$:

$$FS_{PC}(x) = \left(\frac{2PC_1(x)PC_2(x) + T_1}{PC_1^2(x)PC_2^2(x) + T_1}\right) \quad (5)$$

where, $T_1$ is a positive constant to increase the stability of $FS_{PC}$. In practice, $T_1$ can be determined based on the dynamic range of PC values.

2nd Stage of FSIM score is between gradient magnitude, $GM_1$ and $GM_2$ as:

$$FS_{GM}(x) = \left(\frac{2GM_1(x)GM_2(x) + T_2}{GM_1^2(x)GM_2^2(x) + T_2}\right) \quad (6)$$

where, $T_2$ is a positive constant depending on the dynamic range of GM values. In our experiments, both

$T_1$ and $T_2$ will be fixed to all databases so that the proposed FSIM can be conveniently used.

Then, $FS_{PC}$ (x) and $FS_{GM}$ (x) are combined to get the similarity $FS_L(x)$ of $h_1(x)$ and $h_2(x)$. We define $FS_L(x)$ as:

$$FS_L(x) = \left[FS_{PC}(x)\right]^{\alpha} . \left[FS_{GM}(x)\right]^{\beta} \quad (7)$$

where, $\alpha$ and $\beta$ are parameters which are used to adjust the relative importance of PC and GM features. Here we set $\alpha = \beta = 1$ for simplicity. Thus:

$$FS_L(x) = \left[FS_{PC}(x)\right] . \left[FS_{GM}(x)\right] \quad (8)$$

Having obtained the similarity $FS_L(x)$ at each location x, the overall similarity between $h_1$ and $h_2$ can be calculated. It is clear that different locations have different contributions to HVS' perception of the image. For example, edge locations convey more crucial visual information than the location within a smooth area. Since human visual cortex is sensitive to phase congruent structures Henriksson *et al*. (2009), the PC value at a location can reflect how likely it is a perceptibly significant structure point. Intuitively, for a given location x, if anyone of $h_1(x)$ and $h_2(x)$ has a significant PC value, it implies that this position x will have a high impact on HVS in evaluating the similarity between $h_1$ and $h_2$. Therefore, we use:

$$PC_m(x) = \max(PC_1(x), PC_2(x)) \quad (9)$$

To weigh the importance of $FS_L(x)$ in the overall similarity between $h_1$ and $h_2$ and accordingly the FSIM index between $h_1$ and $h_2$ is defined as:

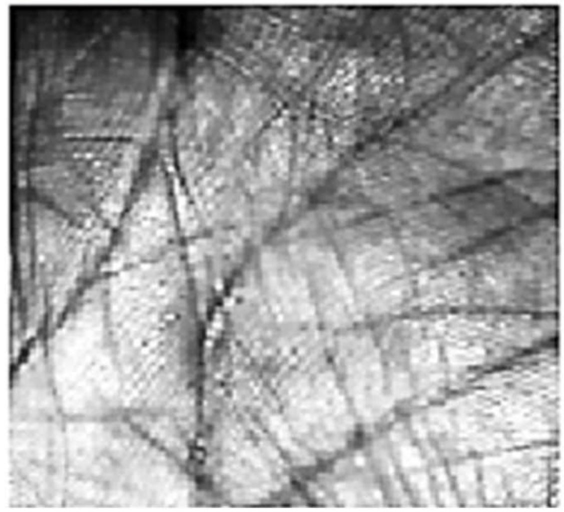
$$FSIM = \frac{\sum_{x\in\Omega} FS_L(x), PC_m(x)}{\sum_{x\in\Omega} PC_m(x)} \quad (10)$$

where, Ω means the whole image spatial domain.

## RESULTS AND DISCUSSION

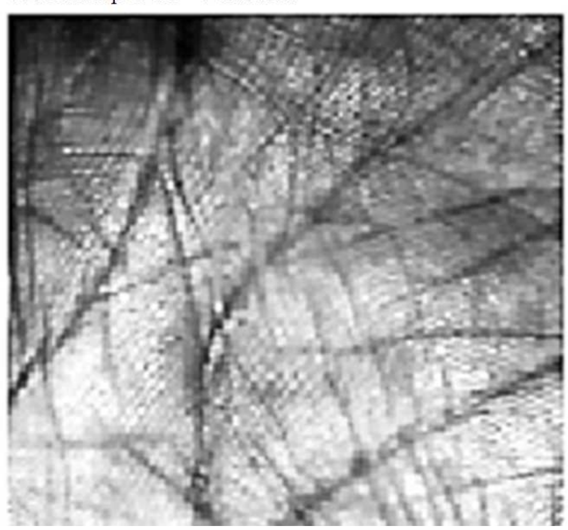
To evaluate the effectiveness of our proposed palm print biometric authentication scheme, a database containing palmprint samples is required. In this study, we use PolyU Palmprint Database (0000) collected by biometric research center at The Hong Kong Polytechnic University, is a widely used database in palmprint research. The database contains 7,752 greyscale images correspond to 386 different palms with 20-21 samples for each in bit map image format. We selected 100 individuals' left hand palm images every person is 5 and total is 500.

Image found (canny) =
000016.bmp score = 97.322501



(a)

Image found (prewitt) =
000016.bmp score = 94.718587



(b)

Fig. 8: Matched image using FSIM (a) Canny FSIM (b) Perwitt FSIM.

Table 1: Accuracy measure

| Methods | Database size | Accuracy |
|---|---|---|
| Proposed method Canny FSIM | 400/100 | 97.322 |
| Proposed method Perwitt FSIM | 400/100 | 94.712 |
| Wavelet transform method (2006) | 100/50 | 96.300 |

Then we get every persons each palm images as a template (total 100).The remaining 400 are as the training samples. The experiments are conducted in MATLAB with image processing Toolbox and on a machine with an Intel core 2duo CPU processor. The test database has 100 different untrained images which undergo the same algorithm as trained image and compare one to one with the original trained image. Using the FSIM algorithm, we calculate the matching score between the test image and trained image. Depending on the best score, corresponding image from the trained database is selected. Fig. 8 shows the Matched image using FSIM, obtained from canny FSIM and Perwitt FSIM respectively. Table 1 show the accuracy of the canny edge and perwitt edge detection technique.

## CONCLUSION

In this study, propose a novel Feature-SIMilarity (FSIM) index and obtain optimum matching score. The experimental results achieve recognition accuracy using canny and perwitt FSIM of 97.3227% and 94.718%, respectively, on the publicly available database of Hong Kong Polytechnic University. Experimental evaluation using palmprint image database clearly demonstrates the efficient recognition performance of the proposed algorithm compared with the conventional palmprint recognition algorithms.

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