Intramodal palmprint recognition using texture feature

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Abstract: Palmprint technology is a new branch of biometrics used to identify an individual. Palmprint has rich set of features like palm lines, wrinkles, minutiae points, texture, ridges, etc. Several line and texture extraction techniques for palmprint have been extensively studied. This paper presents an intramodal authentication system based on texture information extracted from the palmprint using the Haralick features, 2D-Gabor and 2D-log Gabor filters. An individual feature vector is computed for a palmprint using the extracted texture information of each filter type. Performance of the system using three feature types is evaluated individually. Finally, we combine the three feature types using feature level fusion to develop an intramodal palmprint recognition system. The experiments are evaluated on a standard benchmark database (PolyU Database), and the results show significant improvement in terms of recognition accuracy and error rates with the proposed intramodal recognition system compared to individual representations.

Keywords: palmprint; Gabor filter; log-Gabor filter; intramodal; Haralick features; feature level fusion.


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1 Introduction

Biometric-based recognition is the most popular human recognition by their biological features, inherent in each individual. Palmprint-based biometric approach have been intensively developed over the past decade because they possess several advantages such as a rich set of features, high accuracy, high user friendly and low cost over other biometric systems. Palmprint recognition has five stages, palmprint acquisition, preprocessing, feature extraction, enrollment (database) and matching. The major approach for palmprint recognition is to extract feature vectors (FVs) corresponding to individual palm image and to perform matching based on some distance metrics. Palmprint research employs high resolution or low resolution images. Principle lines, wrinkles and texture-based features can be extracted from low resolution images. More discriminate features such as ridges, singular points and minutiae can be extracted using high resolution palm images. In our present work, we have used low resolution images to extract texture features.

Texture-based feature extraction methods are widely adopted for palmprint identification because of their high performance. In the literature, numerous texture-based approaches for palmprint recognition have been proposed. The palmprint textures can be obtained using techniques, such as Gabor wavelets (Wang et al., 2012), Fourier transformation (Imatiaz and Fattah, 2011), cosine transformation (Imatiaz and Fattah, 2011; Dale et al., 2009), wavelet transformation (Khanna and Tamrakar, 2010) and standard deviation (SD) (Gonzalez and Woods, 2009).

In Yazdi and Gheysari (2008), fingerprint image is represented by co-occurrence matrices. Features are extracted based on certain characteristics of the co-occurrence matrix and then fingerprint classification is done using neural networks. Rampun et al. (2013) proposed new texture-based segmentation algorithm which uses a set of features extracted from grey-level co-occurrence matrices. Principal component analysis is used to reduce the dimensionality of the resulting feature space. Gaussian mixture modelling is used for the subsequent segmentation and false positive regions are removed using morphology. An effective Iris recognition system is proposed by Chen et al. (2013). Grey level co-occurrence matrix (GLCM) and multi-channel 2D Gabor filters are adopted to extract
iris features. The combined features are in the form of complementary and efficient effect. Particle swarm optimisation (PSO) is employed to deal with the parameter optimisation for support vector machine (SVM), and then the optimised SVM is applied to classify Iris features.

Palmprint recognition based on Haralick features was proposed by Ribaric and Lopar (2012). Haralick features are extracted from a sub-image and the matching process between the live template and the templates from the system database is performed in N matching modules. Fusion at the matching-score level is used and the final decision is made on the basis of the maximum of the total similarity measure. The experiments are performed on small databases (1,324 hand images). The work in Martins (2013) extracts Haralick features along the principal lines and experiments were evaluated on small part of PolyU database and shows poor performance (EER above 14%). An optimal thenar palmprint classification model is proposed by Zhu et al. (2011). Thirteen textural features of GLCM are extracted and SVM is used for classification. To the best of our knowledge, only few papers on palmprint identification using GLCM were reported in the literature. Most of them have used SVM and k-neural network classifiers and experiments have been performed on small databases and results reported in the literature were not promising.

Research has shown promising results on employing these approaches individually. However, efforts are still required to achieve higher performance for their use in higher security application. These unimodal approaches rely on the evidence of a single source of information for authentication of person. Noisy data, intra-class variation, interclass similarities, non-universality, spoofing, etc., problems are imposed by unimodal biometric systems which tend to increase false acceptance rate (FAR) and false rejection rate (FRR), ultimately reflecting towards poor performance of the system. Some of the limitations imposed by unimodal biometrics can be overcome by integrating palmprint with other biometric modalities (multimodal system) or combine various classifiers (intramodal system) that have shown promising results in palmprint authentication. In intra modal system, multiple algorithms can operate on same biometric trait in order to extract diverse feature set. The use of different feature set makes the system robust to variety of intra-class and inter-class variations. Further, Intra modal biometric provides anti spoofing measure by making it difficult for an intruder to spoof template created by using fusion. In this paper we propose intra modal palmprint recognition. Intramodal systems have the following advantages (Sun et al., 2008; Hao et al., 2007) over unimodal biometric systems

- intramodal system is more reliable due to presence of multiple templates
- intramodal system does not require the use of new sensor and hence cost effective
- the user is not required to interact with multiple sensors thereby enhancing user convenience.
- fusion of the evidence obtained in different form the same or different sources can significantly improve the overall accuracy of the biometric system.
- intramodal biometric can address the problem of non-universality which often occurs in unimodal system.
- the availability of multiple sources of information can reduce the redundancy in unimodal system.
In this paper, we use Haralick features, 2D Gabor and 2D log-Gabor filters to develop an intra-model palmprint recognition system. The rest of the paper is organised as follows. Section 2 discusses the pre-processing and segmentation. Section 3 explains the texture extraction process using Haralick features, 2D of Haralick, Gabor filter and 2D log-Gabor filter. Further, the computation of a feature vector (FV) from the extracted texture and the proposed fusion technique discussed in Section 4. Section 5 describes matching of the palmprints using similarity measure. The experimental results are presented in Section 6. Conclusions are described in Section 7.

2 Preprocessing and segmentation

In this paper, we propose an intramodal palmprint authentication system based on texture features. The proposed method involves pre-processing, feature extraction, feature fusion and matching. Figure 1 shows the basic flow diagram of the proposed method. We used the palmprint database developed at Biometric Research Center at Hong Kong Polytechnic University.

Figure 1 Flow diagram of proposed system
In preprocessing stage, we used technique (Lin et al., 2005) to extract the ROI region. Before extracting the ROI, adaptive median filter (Gonzalez and Woods, 2009) is used to smoothen the image. The advantage of adaptive filter is that it seeks to preserve details while smoothing non-impulse noise, something that the traditional filter does not do. To extract ROI, first the image is rotated 90° in clockwise direction. By scanning the image from the bottom left most pixels the starting point Ps of the bottom line is found. Boundary tracing algorithm is employed to collect the border pixels into a vector called border pixel vector (BVP) as shown in Figure 2(a). Let $W_m$ be the midpoint of the bottom line. Distance to all the pixels from $W_m$ is calculated and distance distribution diagram is plotted as shown in Figure 2(b). Three local mimima are the finger web points. A square region of $150 \times 150$ size is extracted using finger web points as show in Figure 2(c).

Figure 2 (a) Border pixels collected and WM point is shown (b) Distance distribution diagram (c) Finger web points FW1, FW2 and FW3 are found and square region is extracted (see online version for colours)

3 Texture feature extraction

3.1 GLCM matrix and Haralick features

GLCM (Haralick, 1979; Albregtsen, 2008; Eleyan and Demirel, 2009) is a matrix that contains information about the distribution of intensities and information about the
relative position of neighbourhood pixels. As name suggests, it uses greyscale images. Given a greyscale image $I$, the GLCM matrix $P$ is defined as (Haralick, 1979):

$$P(i, j | \Delta x, \Delta y) = WQ(i, j | \Delta x, \Delta y)$$

where $W = 1 / (M - \Delta x)(N - \Delta y)$

$$Q(i, j | \Delta x, \Delta y) = \sum_{n=-\Delta y}^{N-\Delta y} \sum_{m=-\Delta x}^{M-\Delta x} A$$

$$A = \begin{cases} 1 & \text{if } f(m, n) = i \text{ and } f(m + \Delta x, n + \Delta y) = j \\ 0 & \text{elsewhere} \end{cases}$$

where $f(m, n)$ be the intensity at sample $m$, line $n$ of the neighbourhood, $(i, j)$ is the index and $(\Delta x, \Delta y)$ denotes the offset and the orientation respectively. Offset represents the distance between the interested neighbourhood pixels and orientation represents the angle between interested neighbourhood pixels. $Q$ is the summation of $A$. After calculation of GLCM, we do the normalisation by dividing by the multiplication of $M$ and $N$, where $M$ and $N$ are the dimension of the greyscale image $I$.

In our proposed methodology, the local Haralick features are calculated from normalised grey level co-occurrence matrices. Haralick introduced 14 statistical features (Haralick et al., 1973) which are basically texture features which can be extracted from a GLCM matrix. The texture features (Haralick et al., 1973; He et al., 1987) are angular second moment, contrast, inverse difference moment, entropy, correlation, variance, Sum average, sum entropy and, etc. In our investigation four features that can successfully characterise the statistical behaviour (experimentally determined) are.

- **Contrast**: The relative difference between light and dark areas of an image. Contrast is how dark to how light something is. Contrast makes the lighter colours more lighter, and the darker colours darker.

  $$\text{Contrast} = \sum_{n=0}^{G-1} \left( \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} p(i, j) \right) |i - j| = n$$

  where $P$ is GLCM matrix ad $G$ is greyscale value.

- **Entropy**: Entropy measures the disorder or uniformity of greyscale distributions. The entropy is large, when the probability of the greyscale occurrences is same

  $$\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} p(i, j) \log(p(i, j))$$

  where $P$ is GLCM matrix ad $G$ is greyscale value.

- **Variance**: The variance is a measure of how far a set of numbers is spread out. It is one of several descriptors of a probability distribution, describing how far the numbers lie from the mean (expected value).

  $$\text{Variance} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i - \mu)^2 p(i, j)$$

  where $P$ is GLCM matrix ad $G$ is greyscale value, $\mu$ is mean value.
• **Correlation:** Measure that determines the degree to which two pixel values are associated.

\[
\text{Correlation} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \left( i \times j \right) P(i, j) - \left\{ \mu_x \times \mu_y \right\} \sigma_x \sigma_y
\]  

(5)

where \( P \) is GLCM matrix and \( G \) is grayscale value, \( \mu_x, \mu_y \) are mean values and \( \sigma_x, \sigma_y \) are SDs along \( X \) and \( Y \) axis.

\[
\mu_x = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} iP(i, j)
\]

\[
\mu_y = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} jP(i, j)
\]

\[
\sigma_x^2 = \sum_{i=0}^{G-1} (i - \mu_x)^2 \sum_{j=0}^{G-1} P(i, j)
\]

\[
\sigma_y^2 = \sum_{j=0}^{G-1} (j - \mu_y)^2 \sum_{i=0}^{G-1} P(i, j)
\]

GLCM matrices are calculated corresponding to different orientations (0, 45, 90, 135) with four different offset values. The above mentioned four Haralick features are obtained from GLCM matrix created on sub-images of palmprint’s ROI. By calculating this four texture features it is possible to see how they behave for different textures. The size of FV for a biometric template is \( M^*n \) – component FVs, where \( M \) is the number of sub images defined by sliding window on the palmprint’s ROI and \( n \) is the number of local Haralick features.

We have used the following parameters for our experiment: \( M \times M = 150 \times 150 \) dimensions of palmprint ROI, \( g = 256 \) number of grey levels, offset value \( \delta = 1, 2, 3 \) and \( 4 \), \( d \times d = 8 \times 8 \) dimension of sliding window, \( t = 4 \) sliding window translation step and \( \Theta = 0, 45, 90 \) and 135 degrees.

### 3.2 2D Gabor filter

Gabor filters has been extensively studied in the literature to extract texture features from biometrics like fingerprint (Chin et al., 2009), palmprint recognition (Zheng and Sang, 2009; Huang et al., 2009), etc. The advantage with Gabor filters for palmprint is that, the extracted texture information includes principal lines, wrinkles, ridges, etc.

The 2D Gabor filter is a composite function with two components: a Gaussian shaped function and a complex plane wave (Daugman, 1985). It has the following form,

\[
G(x, y, \theta, u, \sigma) = \left( \frac{1}{2\pi\sigma^2} \right) \exp \left\{ -\frac{x^2 + y^2}{2\sigma^2} \right\} \exp \left\{ 2 \pi i \left( \sigma x \cos \theta + y \sin \theta \right) \right\}
\]  

\[
(6)
\]

where \( x, y \) represents the coordinates of the filter, ‘\( u \)’ denotes the filter centre frequency, ‘\( \sigma \)’ is the width of Gaussian envelope, ‘\( \theta \)’ is the orientation of the filter and \( i = \sqrt{-1} \). In the experiment, we chosen the optimised values for Gabor filter parameters empirically and they are: \( u = 0.096, \sigma = 7.1 \) and \( \theta = 45^\circ \).
According to Euler formula, Gabor filter can be decomposed into two parts: real part and imaginary part. The response of a Gabor filter to an image is obtained by a 2D convolution. Let \( I(x, y) \) donate an image and \( I'(x, y) \) denotes the response of the Gabor filter. The Gabor response to an image is defined as follows.

\[
I'(x, y) = I(x, y) \otimes G(x, y)
\]

(7)

The Gabor filtered image has both real and imaginary components. The magnitude of the Gabor filtered image is calculated using,

\[
|I'(x, y)| = \sqrt{\text{Re}I'(x, y)^2 + \text{Im}I'(x, y)^2}
\]

(8)

where \( \text{Re}I'(x, y) \) and \( \text{Im}I'(x, y) \) are the real and imaginary parts of the Gabor filtered image, respectively. The texture information of a palmprint after convolving with the 2D Gabor filter is shown in Figure 3(b).

### 3.3 2D log-Gabor filter

2D log-Gabor filter has been extensively studied to extract the texture features (Fan et al., 2008; Chin et al., 2009). It has the following form,

\[
G(w, v) = \exp\left\{-\frac{\lg(w/w_0)^2}{2[\lg(k)^2]}\right\} \exp\left\{-\frac{\lg(v/v_0)^2}{2[\lg(l)^2]}\right\}
\]

(9)

where \( w_0 \) and \( v_0 \) represents the 2D filter centre frequencies in vertical and horizontal directions respectively, and \( k, l \) are a chosen constant to control the filter bandwidth. The inverse Fourier transform of 2D log-Gabor function is represented as,

\[
g(x, y) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} G(w, v)e^{-j\pi x}e^{-j\pi y}dwdv
\]

(10)

Let an image \( I(x, y) \) is convolved with 2D log-Gabor function [equation (10)] to obtain the log-Gabor filter response \( I'(x, y) \) and is defined as follows.

\[
I'(x, y) = I(x, y) \otimes g(x, y)
\]

(11)

The filtered image \( I'(x, y) \) is complex and has both real and imaginary components. The magnitude of \( I'(x, y) \) is calculated using,

\[
|I'(x, y)| = \sqrt{\text{Re}I'(x, y)^2 + \text{Im}I'(x, y)^2}
\]

(12)

where \( \text{Re}I'(x, y) \) and \( \text{Im}I'(x, y) \) are the real and imaginary parts of the log-Gabor filtered image, respectively. The texture information of a palmprint after convolving with the 2D log-Gabor filter is shown in Figure 3(c).
4 Computation of FV and matching

This section explains the proposed method of computing FV from the extracted texture information for a palmprint image and the matching algorithm.

4.1 Haralick features vector

For the computation of the GLCM not only the displacement (offset value \( \delta \)), but also the orientation between neighbour pixels must be established. The orientations can be horizontal (0\(^\circ\)), vertical (90\(^\circ\)), right diagonal (45\(^\circ\)) and left diagonal (135\(^\circ\)) degree respectively. GLCM matrices for each palmprint’s ROI are calculated corresponding to different orientation (0, 45, 90, 135) with four offset values. The local Haralick features contrast, entropy, variance and correlation are obtained from normalised grey level co-occurrence matrices.

After the calculation of GLCMs, each GLCM is divided into 32 \( \times \) 32 sub-matrices. For each such sub-matrix Haralick features are calculated. There will be 64 such sub-matrices for each such GLCM. Haralick feature of a palmprint ROI is represented by \( N^* \ m \) components given in equation (12).

\[
F_{V_{H}} = N^* \ m
\]

where \( N = 256 \) sub-images and \( m = 4 \) (offset values) \( \times \) 4 (four Haralick features).

Therefore, palmprint ROI is represented by 4,096 features.

4.2 2D Gabor and 2D log-Gabor FV

After extracting the texture information using a particular filter, a FV (or template) is computed for each palmprint image. The convolved ROI palmprint image is segmented into 36 non-overlapping sub images of equal size. Then for each sub image, SD is calculated for both the methods. The FV of size 1 \( \times \) 36 is established. The SDs of all sub images is arranged in raster scan order to generate the FV. \( F_{V_{G}} \) and \( F_{V_{LG}} \) represents FVs of 2D Gabor and 2D log-Gabor method respectively

\[
F_{V_{LG}} = \{SD_1, SD_2, \ldots, SD_{36}\} \quad F_{V_{G}} = \{SD_1, SD_2, \ldots, SD_{36}\}
\]
Intramodal palmprint recognition using texture feature

\[ F_{VLG} = \{SD_1, SD_2, \ldots, SD_{36}\} \]  

(15)

4.3 Fusion of feature vectors

The objective of the data fusion is to improve the performance of the system. The unimodal biometric systems may suffer due to issues such as limited population coverage, less accuracy, matcher limitations, noisy data, etc. (Ross et al., 2006). Hence, unimodal biometrics may not be reliable and to overcome these limitations and improve the performance fusion of multiple biometric information has been proposed. The multiple pieces of biometric evidences can be combined by four fusion strategies:

a. fusion at the sensor level
b. fusion at the feature extraction level
c. fusion at the matching score level
d. fusion at the decision level.

In this paper, we use the feature level fusion Gabor filter and 2D log-Gabor filter. Feature level fusion has richer information about biometric template. Feature level fusion combines the biometric information prior to matching. This level of fusion also reduces the response time than score level fusion. The simplest form of feature level fusion is concatenating the extracted features.

Figure 4 Procedure adopted to perform feature level fusion (see online version for colours)
The individual FVs values of vectors $F_{VH}$, $F_{VG}$, and $F_{VLG}$ may significantly differ in terms of their range and distribution. We have adopted median normalisation (Nanni and Lumini, 2009) technique. Figure 4 depicts the procedure to perform feature level fusion. After normalisation the modified FVs are represented as $F'_{VH}$, $F'_{VG}$ and $F'_{VLG}$. A new $F'_{V}$ is obtained by concatenating $F'_{VH}$, $F'_{VG}$ and $F'_{VLG}$. Next step is to perform matching.

$$F'_{V} = \{F'_{VH}, F'_{VG}, F'_{VLG}\}$$  \hspace{1cm} (16)

5 Matching

The similarity between two given templates can be determined using matching algorithms. Palmprint verification can be done by applying the matching algorithm on the input palmprint image and palmprint existing in the database. We employed Pearson correlation coefficient (Wu and Xu, 2010) to find similarity between two palmprint images in our proposed approach. This approach is most widely used similarity measure. Let $X = \{x_i: i = 1, \ldots, n\}$ and $Y = \{y_i: i = 1, \ldots, n\}$ be the two templates for which we want to calculate the degree of association. The linear correlation coefficient between $X$ and $Y$ is defined by $r(X, Y)$.

$$r(X, Y) = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2}}$$  \hspace{1cm} (17)

where $\bar{x}$, $\bar{y}$ represents the mean of templates $X$, $Y$ respectively and $r$ value lies between $-1$ and $1$. If the value of $r = +1$, it indicates a strong correlation and the two templates are identical, whereas $r = -1$ indicates weak correlation and the templates are perfect opposite.

6 Experimental results

The investigations were performed utilising PolyU Palmprint database (Kumara and Zhang, 2005). PolyU database comprises of 7,752 greyscale palm prints from 193 clients comparing to 386 separate palms. The palm images are edited to 150 × 150 pixels. Experiments have been carried out to evaluate the performance of the proposed fusion method, algorithm based on Haralick features, 2D Gabor features and algorithm based on 2D log-Gabor features. All the techniques have been implemented using MATLAB.

6.1 Performance evaluation criteria

The execution of the proposed framework is resolved utilising four measures, to be specific:
FAR
2 FRR
3 GAR
4 EER.

The FRR indicates the frequency of rejected users who are not imposters. It is one of the most important metrics in a biometric system, since the restriction of access to genuine users is a considerable flaw. It is calculated as:

\[ \text{FRR} = \frac{\text{Total number of actual clients falsely rejected}}{\text{Total number of comparisons}} \times 100 \]

Another important metric is the FAR, which expresses the portion of false identity claims that are incorrectly accepted, by so depicting the frequency of fraudulent accesses. It is defined as:

\[ \text{FAR} = \frac{\text{Total number of imposters falsely accepted}}{\text{Total number of comparisons}} \times 100 \]

GAR is the frequency that an authorised person is accepted as authorised.

\[ \text{GAR} = 100 - \text{FRR} \]

Finally, the EER is defined as the rate at which the FAR is equal to the FRR. A very low number for EER indicates a system with a good balance of sensitivity but is not necessarily the adequate operating point. Specific system requirements could have constraints for a low FAR or FRR value.

6.2 Performance comparison of three individual methods with feature level fusion method

As per literature survey, fusion-based methods will give better accuracy than individual methods. The proposed intramodal palmprint method is a combination of three individual feature methods. Table 1 gives the experimented results of FRR and FAR of Haralick, Gabor, Log Gabor and feature level fusion technique. Plots between various threshold vs FAR and FRR for different techniques are shown in Figure 5. From the plotted curves it can be inferred that FAR and FRR intersect at a point of given threshold value. The intersection of FRR and FAR curves gives EER. It is observed that, the EER of the systems using Haralick features, Gabor and log-Gabor features is 0.23, 0.08 and 0.03 respectively. The analysis of the result shows that the log-Gabor features performs well compared to Haralick feature and Gabor features. The EER of proposed fusion method is 0.02 which is less than Haralick, the Gabor and log-Gabor features methods. The EER values of different methods are tabulated in Table 2.

In order to visually depict the performance of individual methods and proposed fusion technique ROC curve (see Figure 6) is drawn. A ROC curve shows how the FAR values are changed relatively to the values of the GAR and vice-versa. The ROC curve for the proposed methods is given in Figure 6. It is observed that, the proposed fusion system
performs well as GAR is very high and FAR is very low compared to Haralick features, Gabor and log-Gabor based methods.

**Figure 5** Far and FRR at various thresholds for different techniques, (a) Haralick features (b) Gabor features based (c) log-Gabor features based (d) proposed fusion technique (see online version for colours)
Table 1  FAR and FRR rates of Haralick features, Gabor features based, log-Gabor features based, and Proposed Feature level fusion technique

<table>
<thead>
<tr>
<th>Threshold</th>
<th>Haralick features</th>
<th>Gabor features</th>
<th>Log-Gabor features</th>
<th>Feature level fusion</th>
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<tr>
<td></td>
<td>FRR</td>
<td>FAR</td>
<td>FRR</td>
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<tr>
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<td>0.9</td>
<td>0.047</td>
<td>0.5</td>
<td>0.15</td>
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</table>

Table 2  Performance of the different systems on PolyU database

<table>
<thead>
<tr>
<th>Method</th>
<th>EER</th>
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</thead>
<tbody>
<tr>
<td>Haralick features</td>
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<tr>
<td>Gabor features</td>
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<tr>
<td>Log-Gabor features</td>
<td>0.03</td>
</tr>
<tr>
<td>Proposed fusion method</td>
<td>0.02</td>
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</table>

6.3 Performance comparisons with existing intramodal fusion techniques

In order to analyse the performance difference between methods, statistical significance test were conducted. In this paper we use the Z-test statistical method (Wu, 2008).

Let \( ST_1 \) and \( ST_2 \) denote the estimator of the statistic of interest of two methods on two different dataset respectively. The Null and alternate hypothesis are

\[ H_0 : ST_1 = ST_2 \]

\[ H_a : ST_1 \neq ST_2 \]

Then, the Z-statistic can be expressed as

\[ Z = \frac{ST_1 - ST_2}{SE} \]  \hspace{1cm} (18)

where \( SE \) is the standard error difference between two statistic and given by

\[ SE = \sqrt{ST^* (1-ST^*) \left( \frac{1}{n_1} + \frac{1}{n_2} \right)} \]  \hspace{1cm} (19)

where \( ST = \frac{ST_1 * n_1 + ST_2 * n_2}{1/n_1 + 1/n_2} \) and \( n_1 \) and \( n_2 \) are the size of dataset.
From $Z$-values the $p$-values are estimated. We have chosen the significance level to 0.05. Table 3 shows the EERs comparison results among the existing intramodal fusion techniques. The two-tailed $Z$- and $p$-values of two statistic of interest EERs for different existing methods are presented in Table 4. From Table 4, it is found that $p$-values of all existing methods were less than 0.00001. These two-tailed $p$-values are all much less than the 0.05. The null hypothesis is rejected and alternative hypothesis is accepted. Therefore, there is a statistical significant between the existing methods and proposed method.

When compared with the existing works, which uses the Gabor, log-Gabor and Haralick features, the proposed work has shown significant improvement in accuracy because of minimum comparison time and removal of redundant features. Kumar and Zhang (2005), Nanni and Lumini (2009) and Kisku et al. (2010) uses score level fusions for palmprint system and recognition rate is less when compared to Wu et al. (2005) and our proposed method uses feature level fusion. Therefore, feature level fusion shows a better performance than score level fusion.

### Table 3
Comparison with performance of similar intramodal fusion techniques

<table>
<thead>
<tr>
<th>Author and ref</th>
<th>Features extracted</th>
<th>Level of fusion</th>
<th>Fusion technique used</th>
<th>EER (%)</th>
<th>Database size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kumar and Zhang (2005)</td>
<td>Gabor, line and PCA</td>
<td>Score level</td>
<td>Product of sum</td>
<td>3.20</td>
<td>1,000</td>
</tr>
<tr>
<td>Nanni and Lumini (2009)</td>
<td>DCT, LBP and Gabor</td>
<td>Score level</td>
<td>Sum</td>
<td>3.20</td>
<td>700</td>
</tr>
<tr>
<td>Wu et al. (2005)</td>
<td>Texture</td>
<td>Feature level</td>
<td>Wavelet</td>
<td>2.11</td>
<td>3,200</td>
</tr>
<tr>
<td>Kisku et al. (2010)</td>
<td>Gabor</td>
<td>Sensor level</td>
<td>DWT + ACO</td>
<td>3.125</td>
<td>3,600</td>
</tr>
<tr>
<td>Proposed</td>
<td>Gabor, log-Gabor, Haralick features</td>
<td>Feature level</td>
<td>Concatenation</td>
<td>0.02</td>
<td>7,752</td>
</tr>
</tbody>
</table>

### Table 4
The two-tailed $Z$- and $p$-values of two statistic of interest EERs for different existing method compared to proposed method

<table>
<thead>
<tr>
<th>Existing methods</th>
<th>Proposed method</th>
<th>$Z$-values</th>
<th>$p$-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kumar and Zhang (2005)</td>
<td></td>
<td>194.65</td>
<td>&lt; 0.00001</td>
</tr>
<tr>
<td>Nanni and Lumini (2009)</td>
<td></td>
<td>179.80</td>
<td>&lt; 0.00001</td>
</tr>
<tr>
<td>Wu et al. (2005)</td>
<td></td>
<td>206.09</td>
<td>&lt; 0.00001</td>
</tr>
<tr>
<td>Kisku et al. (2010)</td>
<td></td>
<td>155.25</td>
<td>&lt; 0.00001</td>
</tr>
</tbody>
</table>

### 7 Conclusions

This paper proposes an efficient intramodal palmprint authentication system. The technique uses the Haralick features, Gabor and log-Gabor features efficiently to make the system more robust. The individual performance of each feature is evaluated and it is
observed that the log-Gabor features are performed well compared to Haralick features and Gabor features of a palmprint. Finally, Haralick, Gabor and log-Gabor FVs are fused using feature level fusion, and further improve the performance of the authentication system.

Figure 6   ROC curves for different techniques (see online version for colours)

References


