Palmprint Recognition Based on Local Texture Features

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Abstract. In this paper, we propose and evaluate palmprint recognition method based on local Haralick features. The Haralick features are extracted from overlapping square subimages of a palmprint region of interest (ROI). A biometric template is composed of \( N \) \( m \)-component feature vectors, where \( N \) is the total number of overlapping subimages, and \( m \) is the number of local Haralick features per subimage in the ROI. A live biometric template and templates from database are matched in \( N \) matching modules. Based on fusion at the matching-score level, the total similarity measures between a live biometric template and templates from the database are calculated. By using the maximum of total similarity measure and the 1-NN classification rule, the final decision (person identity) is made. The proposed palmprint recognition system was tested on the PolyU database. The results of open set identification are given.

Keywords: Palmprint recognition, local Haralick features, Open set identification

1 Introduction

The palmar surface of a human hand is a rich source of physiological features. High-resolution palmar images (i.e. resolution higher than 500 dpi) offer finger and palmprint recognition based on features such as sweat pores, ridges, singular points and minutia points [1], [2]. From low-resolution palmar images the features such as principle lines (head, life and heart lines), wrinkles and texture-based features can be extracted from palmprint region. These features are relatively stable and unique, and can be used for biometric verification and/or identification.

In general, there are three main approaches to palmprint feature extraction [1]: principal line-based, appearance-based, and statistical-based approach. The principal line-based approach uses different edge detectors to extract palm lines [3]. The most popular group of feature extraction methods for low-resolution palmar images is the appearance-based methods such as principal component analysis (PCA) [4], [5], linear discriminant analysis (LDA) [6], the Most Discriminant Features (MDF) [7], and independent component analysis (ICA) [8].

Statistical approaches are either global or local. The global statistical approaches compute statistical features from the whole original or transformed palmprint region.
of interest (ROI). The local statistical approaches divide the original or transformed palmprint ROI into small regions (subimages) and calculate statistical features for each small region. Recently, more attention has been given to local (statistical) features, such as those extracted from original palmprint images using a Gabor bank of filters [9], and local binary patterns (LBPs) [10].

In this paper, we propose an approach to palmprint recognition based on local Haralick features that are obtained from the gray-level co-occurrence matrices (GLCMs) created on the small overlapping square subimages of the palmprint ROI.

2 Related work

In biometrics applications Haralick features [11], [12] are used for fingerprint classification [13], face [14] and iris recognition [15]. As far as we know, beside our paper [16], there are only four other descriptions of applications of Haralick features for palmprint recognition. In [16] we have described the basic idea of using local Haralick features and results of the series of preliminary palmprint recognition experiments for different parameters of the gray-level co-occurrence matrix (GLCM) for 8 x 8 subimages. The experiments were performed on two relatively small databases (550 hand images of 110 people and 1324 hand images of 133 people). It was shown that the achieved recognition rate (98.91%) was better then the recognition rate for the same databases for the eigenpalm approach. In [17] the author used the Haralick features obtained from relatively large subimages (22 x 22) along the palmprint principal lines. Verification experiments were performed on the small part of the PolyU database (only 50 persons) and have shown a poor performance (EER above 14%). Based on such performance, it may be concluded that the above described approach is not promising. In [18] Zhang et al. have used the image brightness and GLCM based entropy for palmprint aliveness detection. In the contactless palmprint and palm vein recognition system [19], the Haralick features (contrast, variance and correlation) are used for image quality assessment. X. Zhu et al. described palmprint classification based on GLCMs and global Haralick features [20], but the palmprints are classified only into two categories according to traditional Chinese medicine expert knowledge.

3 Local Haralick features

A brief overview of the gray-level co-occurrence matrix (GLCM) and Haralick features substantially follows [11], [12]. The GLCM \( P(g, g', \delta, \Theta) \), size \( G \times G \), contains at the position \((g, g')\) a number of occurrences of a pair of pixels that are at a distance \(\delta\) in the direction \(\Theta\), where one pixel has a gray-level value \(g\), and another pixel has a gray-level value \(g'\). The values of the pixels are quantized into \(G\) levels.

The GLCM has to be normalized in such a way that each element of the matrix is divided by \(R\), where \(R\) is the sum of all the elements in the matrix. An element of the normalized GLCM is the probability of the occurrence of pairs of pixels of imposed values and a fixed spatial layout.
Based on the normalized GLCM, Haralick has proposed 14 statistical features (f₁ - f₁₄), that can be calculated for each δ and Θ [11]: energy (f₁), contrast (f₂), correlation (f₃), variance (f₄), inverse difference moment (f₅), sum average (f₆), sum variance (f₇), sum entropy (f₈), entropy (f₉), difference variance (f₁₀), difference entropy (f₁₁), information measures of correlation (f₁₂ and f₁₃), and maximal correlation coefficient (f₁₄).

In our approach, the local Haralick features are calculated based on the GLCMs created on the d x d pixels subimages; d < D; defined by sliding-windows positioned on the palmprint ROI (size D x D). Sliding-windows define overlapping subimages for the translation step t < d.

The parameters δ, δ = 1, 2, ..., Θ, Θ = 0°, 45°, 90° and 135°; and G have a strong influence on the values of the Haralick features. For example, in the literature [2] there is a recommendation for the values δ (for the global Haralick features) to be from 1 to 8 or 10. Of course, the values of δ depend on the size of the image S and the size and area of the basic texture element. Values of δ, for GLCMs for local Haralick features, are additionally limited by dimension d of the subimage.

In order to obtain features that are robust to rotation and to reduce dimensionality of the feature vectors, we have used the following approach: first, the four GLCMs are obtained (for Θ = 0°, 45°, 90° and 135°), and then a new GLCM is calculated as the average of these four matrices. Finally, the Haralick features are obtained based on this new GLCM.

A number of quantization gray-levels G of an image S is also an important parameter, because the computational complexity for the GLCM and Haralick features (except for f₁₄) is O(G²). At a first glance, the computation of the GLCMs and Haralick features seems a time-consuming process, but the computation can be speeded-up because the matrices are symmetrical, and, in practice, very often sparse.

4 Description of the system

The experimental palmprint recognition system consists of the following modules: preprocessing module, module for localization and normalization of ROI, local Haralick feature extraction module, N matching modules, template database, N distance to similarity transform modules, fusion module, 1-NN and decision module. The short descriptions of functions of the above modules subsequently follow.

4.1 Preprocessing

In the preprocessing module some standard image preprocessing procedures are applied on the input hand-images from PolyU database: global threshold, contour and relevant points extraction. Based on the contour of the hand and the relevant points on it, the palmprint ROI is automatically localized. After that, the ROI is cropped from the gray-scale image, rotated to the same position, sized to the fixed dimensions (96 x 96 pixels) and then it is light normalized using histogram fitting. The procedures of preprocessing are similar to those described in [1]. Light normalization is described in
detail in [5]. We would like to stress that preprocessing is not in the focus of the paper and it is only briefly described.

4.2 Feature extraction

In the feature extraction module, the local Haralick features are extracted from a palmprint ROI as follows. The palmprint ROI represented as a $D \times D$ pixels gray-level image ($D = 96$, $G = 256$ gray levels) is divided into a set of $N$ overlapping subimages. In our implementation, we use the square subimages obtained by using a sliding-window approach. A sliding-window of the size $d \times d$ pixels is positioned in the upper-left corner of the ROI. The first subimage is composed of all the pixels of a palmprint ROI that fall inside the window. After that, the window is translated by $t = d / 2$ pixels to the right, and so on. When the sliding-window falls outside of the palmprint ROI, it is moved $t$ pixels down and all the way to the left of the ROI. The process is concluded when the bottom-right corner of the sliding-window reaches the bottom-right corner of the palmprint ROI. Each sliding-window position defines one of $N$ regions (subimages). The total number of the subimages is:

$$N = \left( \left\lfloor \frac{D-d}{t} \right\rfloor + 1 \right)^2$$

(1)

For a 96 x 96 pixels palmprint ROI and for a 12 x 12 pixels sliding-window, and sliding-window translation step $t = 6$ pixels, there are $N = 225$ subimages.

Based on exhausting testing, by using our own databases FER I (550 hand images of 110 people, 5 templates per person) and FER II (1324 hand images of 133 people, approximately 10 templates per person) [16]; FER I $\cap$ FER II = $\emptyset$; we have found that:

i) three local Haralick features (energy, contrast, correlation) are sufficiently discriminatory for palmprint recognition purposes,

ii) the size of the sliding-window $d = 12$, the sliding-window translation step $t = 6$ and the distances $\delta$ from 1 to 6, give satisfactory recognition accuracy,

iii) the number of gray-levels of the palmprint ROI which is less than $G = 128$ degrades the recognition accuracy. We have selected $G = 256$ levels.

iv) the recognition accuracy becomes lower if the resolution of the palmprint ROI is decreasing. The resolution 96 x 96 was selected.

The three selected local Haralick features are defined as follows:

Energy:

$$f_i = \sum_{g=0}^{G-1} \sum_{g'=0}^{G-1} (p(g, g'))^2$$

(2)
Contrast:

\[ f_2 = \sum_{g=0}^{G-1} \sum_{g'.tbl.19}^{G-1} (g - g')^2 p(g, g') \]  

Correlation:

\[ f_3 = \frac{1}{\sigma_x \sigma_y} \sum_{g=0}^{G-1} \sum_{g'=0}^{G-1} (gg')p(g, g') - \mu_x \mu_y \]  

where 

\[ \mu_x = \sum_{g=0}^{G-1} p_x (g), \quad p_x (g) = \sum_{g'=0}^{G-1} p(g, g') \quad \mu_y = \sum_{g=0}^{G-1} p_y (g), \quad p_y (g) = \sum_{g'=0}^{G-1} p(g, g') \]

\[ \sigma_x = \sqrt{\sum_{g=0}^{G-1} p_x (g)(g - \mu_x)^2}, \quad \text{and} \quad \sigma_y = \sqrt{\sum_{g=0}^{G-1} p_y (g)(g - \mu_y)^2}. \]

Based on the above selected parameters, a palmprint ROI is represented by \( N \) \( m \)-component feature vectors, where \( N = 225 \) and \( m = 6 \times 3 \), where 6 is a number of distances and 3 a number of local Haralick features. Each biometric template is represented by 4050, i.e. 225 \( \times \) 18, features.

4.3 Matching, fusion at the matching-score level and decision

The matching process between the \( m \)-component feature vector (\( m = 18 \)), which is a component of the live template, and the corresponding \( m \)-component feature vector - a component of the template from a database, is performed in a matching module using the Euclidean distance. There are \( N \) matching modules. Note that the values of the feature vector components are within different dynamic ranges (from \( 10^{-2} \) to \( 10^3 \)) and the normalization of the features has to be applied before any calculation of the Euclidean distance. A straightforward technique of linear normalization via the respective estimates of the mean and the variance is used (z-score normalization).

The outputs of the matching modules are transformed into the similarity measures \( s_{ij}, i = 1, 2, \ldots, N \) as follows:

\[ s_{ij} = \begin{cases} 1 - \frac{d^{e}_{ij}}{d^{e}_{max}}, & \text{if } d^{e}_{ij} \leq d^{e}_{max} \\ 0, & \text{if } d^{e}_{ij} > d^{e}_{max} \end{cases} \quad \forall i = 1, 2, \ldots, N \]

where \( d^{e}_{ij} \) is the Euclidean distance between the \( m \)-component feature vector obtained from the subimage \( i \) from the live template, and the corresponding \( m \)-component feature vector from the \( j \)-th database template. The distance \( d^{e}_{max} \) is the maximum distance of the corresponding \( m \)-component feature vectors, for subimage \( i \), which is obtained from the training set.
In the proposed experimental system we used fusion at the matching-score level, so the similarity measures obtained from $N$ matchers are combined.

The total similarity measure $TSM_j$ between the live template and the $j$-th database template is:

$$TSM_j = \sum_{i=1}^{N} w_i s_{ij}$$

(6)

where $w_i, i = 1, 2, \ldots, N$, is the weight assigned to the subimage $i$. The weights $w_i, i = 1, 2, \ldots, N$, are set proportionally to the results of the recognition rate for each subimage $i$ during the evaluation of the system:

$$\sum_{i=1}^{N} w_i = 1$$

(7)

$$w_i = \frac{\text{recognition}\_\text{rate}_{i}}{\sum_{j=1}^{N} \text{recognition}\_\text{rate}_{j}}$$

(8)

where $\text{recognition}\_\text{rate}_{i}$ is a recognition rate for the subimage $i$.

Note that the weights $w_i, i = 1, 2, \ldots, N$ are calculated from the training set ($PolyU_1$ database; see Section 5.).

By using the 1-NN classification rule based on the maximum $TSM_j$, the final decision (person identity) based on a decision threshold is made.

5 Experiments and results

For the development, evaluation and testing of the proposed experimental palmprint recognition system we used the database $PolyU$ [22], which consists of 7751 palmprint images of 386 persons (about 20 images per person). The syntax of the palmprint image notation is "$PolyU\_xxx\_L\_NN.bmp"", where $xxx$ denotes ID of palmprint (001 - 386), $L$ denotes session (F - first, S - second) and $NN$ denotes the number of the palmprint image (01 - 20). The database $PolyU$ was divided in three sub-databases: $PolyU_k; k = 1, 2, 3$.

In order to determine the values of the weights $w_i, i = 1, 2, \ldots, N$, associated with each subimage, we used a training database $PolyU_1$, (2401 palmprint images of 120 people; ID = 1 to 120).

The following operations are performed:

1) For all the samples in the database $PolyU_1$, all the features are calculated according to parameters selected in advance ($d, t, \delta, G$, a number of local Haralick);

2) The separated template (the active sample) is matched with all the remaining templates in the $PolyU_1$. The features obtained from the subimages of the active samples are compared to the features obtained from the corresponding subimages of the samples in the database. For example, the local Haralick features, extracted from the
subimage defined by the sliding-window positioned in the upper-left corner of the palmprint ROI for the active sample, are matched with features obtained from the upper-left corner of the palmprint ROI from all the other samples in the PolyU1.

3) The 1-NN classification of the active sample is made for each subimage and the result of the correct classification is recorded.

The above procedure is repeated for all samples in the database PolyU1. The values of the weights \( w_i, i = 1, 2, \ldots, N \), are calculated according to the equation (8).

### 5.1 Open set identification experiment

For the open set identification experiment we used the PolyU2 database (931 palmprint images of 156 people; about 6 images per person - 3 from F, and 3 from S session; ID = 121 to 276) and the PolyU3 database (4419 palmprint images - 2201 palmprint images of 156 users (about 14 images per user; ID 121 - 276; plus 2218 palmprint images of 110 people which have role as impostors; ID 277-386.)

This set up makes for 2201 client experiments (about 156 x 14) and 2218 impostor experiments (about 110 x 20).

The open set identification experiment was repeated 20 times for 6 different client templates (3 from the first session, 3 from the second session) in the template database.

The results of the open set identification are represented in terms of FAR (False Accepted Rate), FRR (False Rejection Rate), and FIR (False Identification Rate):

- **FAR [%]** = (# of accepted imposters as clients) x 100 / (total # of imposters),
- **FRR [%]** = (# of rejected clients) x 100 / (total # of clients),
- **FIR [%]** = (# of wrongly classified clients) x 100 / (total # of clients).

Table 1. shows the mean value and standard deviation for FAR, FRR and FIR as a function of the threshold \( T \).

<table>
<thead>
<tr>
<th>Threshold T</th>
<th>FAR (mean [%]; std. deviation [%])</th>
<th>FRR (mean [%]; std. deviation [%])</th>
<th>FIR (mean [%]; std. deviation [%])</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.884</td>
<td>6.73; 0.500</td>
<td>1.30; 0.335</td>
<td>0.09; 0.032</td>
</tr>
<tr>
<td>0.885</td>
<td>4.61; 0.281</td>
<td>1.37; 0.334</td>
<td>0.09; 0.028</td>
</tr>
<tr>
<td>0.886</td>
<td>3.20; 0.243</td>
<td>1.44; 0.342</td>
<td>0.06; 0.018</td>
</tr>
<tr>
<td>0.887</td>
<td>2.05; 0.212</td>
<td>1.53; 0.334</td>
<td>0.06; 0.026</td>
</tr>
<tr>
<td><strong>0.888</strong></td>
<td><strong>1.32; 0.143</strong></td>
<td><strong>1.64; 0.335</strong></td>
<td><strong>0.04; 0.026</strong></td>
</tr>
<tr>
<td>0.889</td>
<td>0.88; 0.135</td>
<td>1.73; 0.342</td>
<td>0.04; 0.026</td>
</tr>
<tr>
<td>0.890</td>
<td>0.57; 0.145</td>
<td>1.82; 0.383</td>
<td>0.04; 0.030</td>
</tr>
<tr>
<td>0.891</td>
<td>0.30; 0.088</td>
<td>1.93; 0.393</td>
<td>0.04; 0.030</td>
</tr>
<tr>
<td><strong>0.892</strong></td>
<td><strong>0.13; 0.036</strong></td>
<td><strong>2.05; 0.424</strong></td>
<td><strong>0.04; 0.030</strong></td>
</tr>
<tr>
<td>0.893</td>
<td>0.09; 0.038</td>
<td>2.19; 0.421</td>
<td>0.02; 0.024</td>
</tr>
<tr>
<td>0.894</td>
<td>0.06; 0.026</td>
<td>2.37; 0.450</td>
<td>0.02; 0.024</td>
</tr>
<tr>
<td>0.895</td>
<td>0.01; 0.021</td>
<td>2.51; 0.507</td>
<td>0.02; 0.024</td>
</tr>
</tbody>
</table>
Fig. 1 presents the open set identification test results and shows the dependence of the FAR and the FRR on the threshold value $T$. From Fig. 1, and Table 1 it is clear that our identification system achieves EER (Equal Error Rate; $\text{FAR} \approx \text{FRR}$) equal to $(1.32 \% \pm 0.143 \%$ and $1.64 \% \pm 0.335 \%)$ for threshold $T = 0.888$. For the same threshold value, the false identification rate $\text{FIR}$ is $0.04\% \pm 0.026 \%$.

A minimal total error $\text{TER} = \text{FAR} + \text{FRR}$ is $2.18 \%$, where FAR is $0.13\% \pm 0.036 \%$ and FRR is $2.05 \% \pm 0.424 \%$, is achieved with the threshold value 0.892. At the same time false identification rate $\text{FIR}$ is $0.04 \% \pm 0.030 \%$. Fig. 2 shows the ROC curve.
5.2 Identification time

The total identification time per person consists of a fixed time, which is required for the hand-image preprocessing, ROI extraction, normalization, feature extraction, and a variable time for the one-to-many matching process:

\[ \text{total identification time} = \text{fixed time} + M \times (\text{one-to-one matching time}), \]

where \( M \) is the number of all the templates stored in the database during the enrolment process. The fixed time is 172 ms and the time for one-to-one matching is 0.070 ms for a personal computer (one-core processor, working frequency 2.40 GHz, 1066 MHz FSB).

6 Conclusion

We have developed an experimental palmprint recognition system based on local Haralick features. For open set identification, based on PolyU database, the following results are achieved: EER (FAR-FRR) is (1.32 % ± 0.143% and 1.64 % ± 0.335 %) for threshold \( T = 0.888 \), a minimal total error TER is 2.18 %, where FAR is 0.13% ± 0.036 % and FRR is 2.05 % ± 0.424 %, at threshold value \( T = 0.892 \). At the same time false identification rate FIR is 0.04% ± 0.030%.

Compared with the approach based on the features obtained from a palmprint by means of an LBP operator applied on a Gabor response [23], for the same database, our experimental system achieved better results in terms of the recognition accuracy and the computational speed.

References