Palmprint Recognition Based on Local Haralick Features

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***Abstract* -- In this paper we propose a novel approach to palmprint recognition based on local Haralick features. These features are calculated from the grey-level co-occurrence matrices created on the d x d pixels subimages of the D x D pixels palmprint region of interest (ROI); $d < D$ defined by overlapping sliding-windows. The biometric template for a person consists of N m-component feature vectors, where N is the total number of subimages and m is the number of Haralick features extracted from a subimage. In order to identify a person, 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 results of the recognition and open-set identification experiments are given.**

***Index terms* -- biometrics, palmprint recognition, local Haralick features**

I. INTRODUCTION

The human hand is the source for a number of physiological biometric features, among which the most commonly used are dermatologlyptic patterns of the fingerprints and palmprints [1], [2], [3]. The palmprint features obtained from visual images can be classified into three main types of features: principal lines, wrinkles and ridges. These principal lines, wrinkles and ridges define the palmprint's region of interest (ROI) as a texture containing discriminatory features that are relatively stable and can be used by biometric-identification or verification systems.

The most popular group of feature-extraction methods for palmprint recognition is the appearance-based methods, such as principal component analysis (PCA) [4], [5], linear discriminant analysis (LDA) [6], their various modifications (MDF, RD-LDA) [7], and independent component analysis (ICA) [8]. Recently, even more attention has been given to local features, such as those extracted using a Gabor bank of filters [2], [9] and local binary patterns [10], [11]. These local features are more robust to light variance and can give better recognition accuracy than global features.

In this paper we present an experimental palmprint recognition system based on local Haralick features.

The Haralick features [12], [13], were used for image classification and retrieval [14], fingerprint classification [15], [16], face [17], and iris recognition [18]. To the best of our knowledge, no one has yet tested local Haralick features in palmprint-recognition tasks. As far as we know, there is only one application of the global Haralick features for palmprint, but they are only used for aliveness detection [19].

II. GRAY LEVEL CO-OCCURRENCE MATRIX AND HARALICK FEATURES

Among the many different statistical approaches to the measurement and characterization of image texture, Haralick's approach is one of the most popular. Haralick features extracted from an image texture are obtained from the grey-level co-occurrence matrices (GLCMs) that contain information about the statistical distribution of grey levels in the analysed image [12], [13]. The co-occurrence matrix $P(g, g', \delta, \Theta)$, size G x G, where G is a cardinality of a set of quantizied grey-level values L_G of an image, contains at the position (g, g'), a number of occurrences of a pair of pixels that are at a distance $\delta = 1, 2, 3, \ldots$, in the direction $\Theta = 0^0$, 45^0, 90^0, 135^0, where one pixel has a grey-level value $g \in L_G$, and another pixel has a grey-level value $g' \in L_G$. 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. Based on the normalized GLCM, Haralick has proposed 14 statistical features, called Haralick features, that can be calculated for each δ and Θ [12].

In our approach the local Haralick features are obtained from the normalized grey-level co-occurrence matrices (GLCMs) created on the d x d pixels overlapping subimages of the palmprint's D x D ROI, $d < D$ defined by a sliding-window that slides on the palmprint's ROI with a translation step $t = d/2$ pixels. Based on series of preliminary recognition experiments we have selected the following

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parameters: D x D = 64 x 64 - dimension of palmprint ROI; G = 256 - number of grey-levels; d x d = 8 x 8 - dimension of sliding-window; t = 4 - sliding-window translation step; and δ = 1, 2, 3, 4 - distances of the pixels. In order to reduced the dimensionality of the feature vector, instead of using four GLCMs for the angular relationships between two neighboring pixels: $\Theta = 0^0, 45^0, 90^0$ and 135^0, we used one GLCM which is calculated as the average of these four matrices.

Preliminary palmprint recognition experiments have shown that only three Haralick features [12], [13]:

i) energy:

$$f_1 = \sum_{g=0}^{G-1}\sum_{g'=0}^{G-1}\left(p(g,g')\right)^2$$

ii) contrast:

$$f_2 = \sum_{g=0}^{G-1}\sum_{g'=0}^{G-1}(g-g')^2\, p(g,g')$$

iii) 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 $\mu_x = \sum_{g=0}^{G-1} g p_x(g)$, $p_x(g) = \sum_{g'=0}^{G-1} p(g,g')$,

$$\mu_y = \sum_{g=0}^{G-1} g p_y(g),\; p_y(g') = \sum_{g=0}^{G-1} p(g,g'),$$

$$\sigma_x = \sqrt{\sum_{g=0}^{G-1} p_x(g)(g-\mu_x)^2}, \text{ and}$$

$$\sigma_y = \sqrt{\sum_{g=0}^{G-1} p_y(g)(g-\mu_y)^2}.$$

give the best recognition rate.

Based on above selected parameters and local Haralick features a palprint ROI is represented by N m-component feature vectors, where N = 225 is the total number of subimages and m = 4 x 3, where 4 is number of distances and 3 is number of local Haralick features.

III. DESCRIPTION OF THE EXPERIMENTAL PALMPRINT-RECOGNITION SYSTEM

Fig. 1 shows the architecture of the experimental palmprint-recognition system based on local Haralick features. In the image-acquisition phase, an image of the palmar surface of the right hand is taken using a desktop scanner (180 dpi, 256 grey levels). The user puts a hand on the scanner with the fingers spread naturally; there are no pegs, or any other hand-position constrains. In the pre-processing module some standard image pre-processing procedures are applied: global thresholding, contour and relevant points extraction. Based on the contour of the hand and the relevant points on it, the palmprint region of interest (ROI) is automatically localized. After that, the ROI is cropped from the grey-scale image, rotated to the same position, sized to the fixed dimensions (64 x 64 pixels) and then it is light normalized using histogram fitting. The procedures of pre-processing and light normalization, and automatic ROI localization are described in detail in [5].

In the feature-extraction module, the local Haralick features are extracted from a palmprint's ROI. The biometric template consists of N m-component feature vectors, where N is the number of subimages defined by the sliding-windows positioned on the palmprint's ROI and m is the number of local Haralick features. In the subsequent N matching modules, the matching between the live template and the templates from a system database based on the Euclidean distance is performed. After the transformation of the matching scores into similarities, fusion based on the weighted-sum rule is applied. In the decision module the final decision is made by using the 1-NN classification rule.

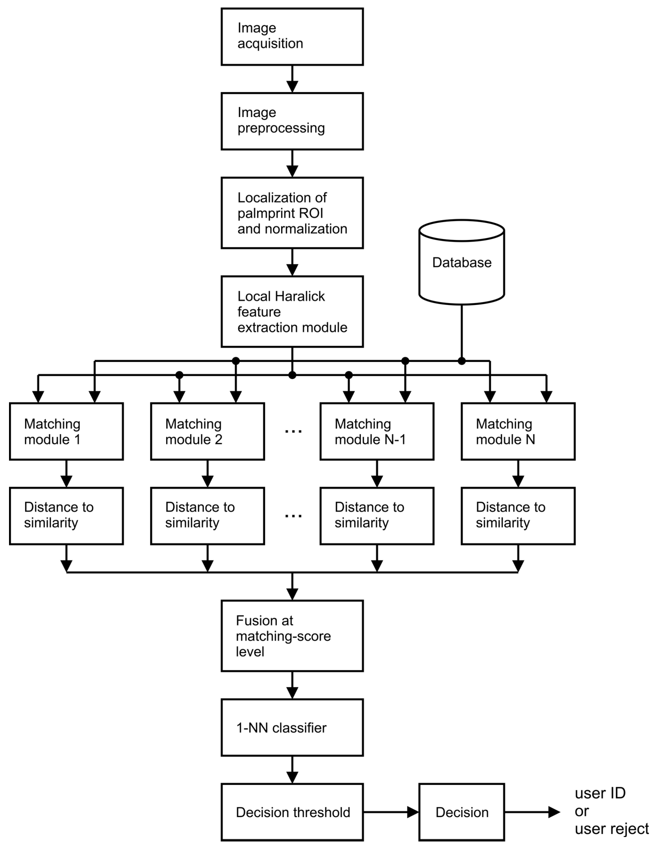

Fig. 1. Architecture of the experimental palmprint-recognition system based on the local Haralick features

IV. EXPERIMENTS AND RESULTS

For the development, evaluation and testing of the proposed experimental palmprint-recognition system we used two databases: Database I (DB I) contains 550 hand images of 110 people (five images per person) and Database II (DB II) contains 1324 hand images of 133 people (approximately ten images per person). Both databases were collected over a period of six months. The interval over which the images of an individual person were acquired varied, with some persons giving all their samples at one time, and the others over a period of up to two months. There is no person which is included in the both databases (DB I $\cap$ DB II = $\varnothing$).

DB I was used as a training database for the selection of the parameters of the recognition system, while DB II was used for the open-set identification.

Experiment 1

In order to determine the values of the weights w_i, i = 1, 2, ... , N, associated with each subimage that will be used in he process of matching-score fusion, the following operations are performed:

1) For all the samples in the database DB I, all the features are calculated according to parameters selected in advance ($d = 8$, $t = 4$, δ = 1, 2, 3 and 4, G = 256, and three local Haralick features: f_1, f_2 and f_3);

2) The separated template (the active sample) is matched with all the remaining templates in DB I;

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's ROI for the active sample is matched with features obtained from the upper-left corner of the palmprint's ROI from all the other samples in DB I.

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

Fig. 2 shows the values of the weights w_i, i = 1, 2, ..., 225 for each subimage of the palmprint's ROI. The weights w_i, i = 1, 2, ..., 225 are set according the recognition rate for every subimage and used for evaluation of the total similarity measure TSM_j between the live template and the j-th database template:

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

where s_{ij} is the similarity measure between the m-component feature vector obtained from the subimage i from live template, and the corresponding m-component feature vector from j-th database template. The similarity measures are obtained as follows:

$$s_{ij} = \begin{cases} 1 - \dfrac{d^e{}_{ij}}{d^e{}_{i\max}}, & if\ d^e{}_{ij} \le d^e{}_{i\max} \\ 0, & if\ \ d^e{}_{ij} > d^e{}_{i\max} \end{cases} \qquad \forall i = 1,2,...,N$$

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 $d^e_{i\max}$ is the maximum distance of the corresponding m-component feature vectors, for subimage i, which is obtained from the training set.

Experiment 2

The palmprint recognition experiment for DB I was carried out based on the leave-one-out approach: we take the first template (the active template) from the database and separate it from the rest. This template is then matched to all the templates remaining in the database. The simple criterion of minimum Euclidean distance is used for the recognition. After this, the separated template is returned to the database, the next template is separated, and the process described above is repeated until every template in the database is matched with the remainder of the database. The achieved recognition rate was 98.91% and it was better then the palmprint recognition rate for the same database for the system based on eigenpalm approach [5].

Experiment 3

For the open-set identification experiment we used DB II (1324 hand images of 133 people) in such a way that it is divided into two parts: a client database and an impostor database. In this experiment, 63 people were selected to act as clients. The first seven hand images from each client were used in the enrolment to generate a client-template database (except for one client, where six hand images were used). The total number of client templates in the database is 440, i.e., 62 x 7 + 6.

The remaining three hand images were used for the testing. There were 189 hand images of people declared as clients, i.e., 63 x 3. The remaining 70 people, ten hand images per person, had the role of impostors (except for five impostors, where nine hand images were used). This set-up makes for 189 client experiments (63 x 3) and 695 impostor experiments (65 x 10 + 5 x 9).

The achieved EER (FAR-FRR) was (1.58% - 2.12%) for open-set identification at the threshold 0.750.

The identification time on a personal computer (working frequency 2.40 GHz, 1066 MHz FSB and 8M cache) was 176 ms per person.

5.11	3.53	3.67	2.95	4.68	4.68	3.82	3.96	2.59	3.46	3.96	4.25	3.67	3.53	4.03
3.74	3.67	3.17	1.94	3.60	3.89	4.32	3.10	4.25	4.32	3.02	4.10	3.31	3.02	2.81
3.38	2.52	2.88	3.17	4.32	6.55	6.48	7.27	7.06	4.90	4.68	3.89	3.10	3.67	3.53
3.96	4.32	4.46	7.06	8.78	10.15	7.27	7.70	7.13	7.06	4.75	5.76	6.70	7.63	5.69
4.32	4.82	6.48	6.34	**10.87**	9.86	8.71	8.14	7.42	9.58	8.50	6.62	8.93	7.20	8.28
4.10	4.39	4.32	6.84	5.61	8.21	7.34	8.28	10.08	9.94	8.42	8.71	7.99	7.63	8.14
2.66	2.66	2.30	5.11	5.76	6.48	5.18	7.49	8.28	7.49	6.62	4.46	5.18	5.98	5.76
2.59	3.17	4.03	3.60	4.82	5.04	5.90	3.96	5.26	4.75	4.18	3.82	3.67	4.68	6.84
2.66	3.02	3.02	4.90	3.74	3.60	4.18	4.25	2.81	2.59	3.53	3.10	4.25	4.32	5.90
2.74	2.74	4.54	3.67	3.60	4.46	5.04	4.03	4.03	2.59	3.60	4.10	4.32	3.82	6.12
2.88	2.81	2.59	4.03	2.45	4.10	5.18	3.60	2.81	4.46	3.02	3.60	3.24	1.80	4.25
3.02	3.31	3.02	3.67	4.32	4.18	4.90	3.60	3.31	4.25	2.30	3.24	2.81	3.10	3.60
2.88	2.16	2.66	3.31	3.38	3.67	4.03	2.59	3.24	3.46	2.52	2.16	2.88	2.74	3.31
4.10	3.38	2.81	2.88	3.67	3.67	4.25	2.38	2.95	2.74	1.73	2.38	2.38	3.17	1.94
2.59	3.89	2.88	3.53	3.96	3.82	3.02	2.30	2.45	2.38	1.94	2.23	2.38	2.30	2.38

Fig. 2. Values of weights assigned to each of the 255 subimages (x 10^{-3})

V. CONCLUSION

We have developed an experimental palmprint-identification system based on local Haralick features. The palmprint's ROI is divided into a set of *N* overlapping regions (subimages). For each subimage, based on the grey-level co-occurrence matrices, the local Haralick features are extracted. The whole template is represented by *N* *m*-component feature vectors, where *m* is the number of local Haralick features extracted from a subimage. The recognition result 98.91% was achieved for the 8 x 8 sliding-window, window translation step 4 pixels, distances from 1 to 4, 256 grey levels of a 64 x 64 palmprint ROI, and 3 local Haralick features (energy, contrast, correlation). In this case the palmprint ROI is represented by 2700 features (3 local Haralick features x 4 distances x 225 subimages). The achieved recognition rate is better then the palmprint recognition rate for the same database for the recognition system based on eigenpalm approach [5].

The achieved open-set identification results was EER (FAR – FRR) = (1.58 % - 2.12 %) at threshold 0.750.

In the future, we plan to test the experimental recognition system on large palmprint database PolyU and to compare the results with system based on LBP operator applied on a Gabor response [11]. Also, we would like to investigate how the LDA applied on local Haralick features and local binary LDA [20] influence the results of the identification and the identification time.

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