Palmprint Recognition Based on Local Haralick Features*

Prof. Slobodan Ribarić, PhD.
Markan Lopar, Dipl.-Ing.
slobodan.ribaric@fer.hr

Laboratory of Pattern Recognition and Biometric Security Systems (RUBIOSS)

University of Zagreb,
Faculty of EE and Computing (FER)
Croatia

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LOCATION

Zagreb, Croatia
ZAGREB

• Capital of Croatia

• Situated at the foot of the Medvednica Mountain on the banks of the river Sava

• An ancient city of about 1,000,000 inhabitants

• Located in the very heart of Europe, on the border between the Mediterranean, Central Europe and the European Southeast
Adriatic Sea, 5835 km seacoast, 1246 island
Overview

1. Introduction
2. Gray level co-occurrence matrix and Haralick features
3. Experimental palmprint-recognition system
4. Experiments and results
5. Conclusion
1. Introduction

Palmprint features obtained from visual images can be classified into three main types of features:

- principal lines
- wrinkles and
- ridges
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.

ROI 64 x 64 pixels

Size: 21x24 cm
Resolution: 600 dpi
Bit level: 8 bit, 256 gray levels
Feature-extraction methods for palmprint recognition:

• principal component analysis (PCA)
• linear discriminant analysis (LDA)
• their various modifications (MDF, RD-LDA)
• independent component analysis (ICA)
• Gabor bank of filters and
• local binary patterns (LBP)

Local features are more robust to light variance and can give better recognition accuracy than global features.
Our idea was to use Haralick local features for palmprint recognition.

Haralick features (1974.) were used for:

- image classification and retrieval,
- fingerprint classification
- face recognition
- iris recognition
2. Gray level co-occurrence matrix and Haralick features

- statistical approach to the measurement and characterization of image texture

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.
The grey-level co-occurrence matrix $P(g, g', \delta, \Theta)$, size $G \times G$, where:

$G$ is a cardinality of a set of quantized 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 $\Theta = 0^\circ, 45^\circ, 90^\circ, 135^\circ$, where one pixel has a grey-level value $g \in L_G$, and another pixel has a grey-level value $g' \in L_G$.

Normalized grey-level co-occurrence matrix (GLCM) – 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 $\delta$ and $\Theta$.

In our approach the **local Haralick features** are obtained from the normalized grey-level co-occurrence matrices (GLCMs) created on the $d \times d$ pixels overlapping subimages of the palmprint’s $D \times D$ ROI, $d < D$ defined by a sliding window that slides on the palmprint’s ROI with a translation step $t = d/2$ pixels.
In our approach the following parameters are selected:

- $D \times D = 64 \times 64$ - dimension of palmprint ROI;
- $G = 256$ - number of grey-levels;
- $d \times d = 8 \times 8$ – dimension of sliding-window;
- $t = 4$ - sliding-window translation step; and $\delta = 1, 2, 3, 4$ 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 neighbouring 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 give the best recognition rate:

- **energy**
  \[ f_1 = \sum_{g=0}^{G-1} \sum_{g'=0}^{G-1} (p(g, g'))^2 \]

- **contrast**:
  \[ f_2 = \sum_{g=0}^{G-1} \sum_{g'=0}^{G-1} (g - g')^2 p(g, g') \]

and
• correlation:

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

where

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

\[ \mu_y = \sum_{g=0}^{G-1} g p_y (g) \]
\[ p_y (g') = \sum_{g=0}^{G-1} p(g, g') \]
Based on above selected parameters and local Haralick features a palmprint ROI is represented by $N$ $m$-component feature vectors, where $N = 225$ is the total number of subimages and $m = 4 \times 3$, where 4 is number of distances and 3 is number of local Haralick features.

- ROI is characterized by 2700 features
3. Experimental palmprint-recognition system

- **image acquisition:**
  desktop scanner (180 dpi, 256 grey levels)

- **image preprocessing:**
  global thresholding, contour and relevant points extraction, ROI localization, ROI geometric and light normalization

- **local Haralick feature extraction**
• matching:
  live template and the templates from a system database - Euclidean distance

• distance to similarity transformation

• fusion at matching score level:
  weighted-sum rule \( TSM_j = \sum_{i=1}^{N} w_i s_{ij} \)

• classification:
  1-NN classification rule
4. Experiments and results

Experimental set-up

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)

$$DB\ I \cap DB\ II = \emptyset$$

DB I was used as a training database for the selection of the parameters of the recognition system

DB II was used for the open-set identification
Experiment 1

In order to determine the values of the weights $w_i$, $i = 1, 2, \ldots, N$, associated with each subimage that will be used in the process of matching-score fusion, the DB I is used.

For the following parameters:
$d = 8$, $t = 4$, $\delta = 1, 2, 3$ and $4$, $G = 256$,
and three local Haralick features: $f_1$, $f_2$ and $f_3$ the weights $w_i$, $i = 1, 2, \ldots, N$, are determined.
Values of weights assigned to each of the 255 subimages (x 10^-3)

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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.

- recognition rate was 98.91%

/better then the palmprint recognition rate for the same database for the system based on eigenpalm approach/
Experiment 3

For the open-set identification experiment we used DB II (1324 hand images of 133 people)

- a client database: 63 people were selected to act as clients (7 database templates per user, 3 live client templates per user)

- an impostor database: 70 people as imposters (695 imposter templates)

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

- an experimental palmprint-identification system based on local Haralick features was proposed
- the palmprint’s ROI is divided into a set of \( N \) overlapping regions (subimages); \( N = 225 \)
- based on the grey-level co-occurrence matrices, the local Haralick features (energy, contrast, correlation) are extracted
- ROI is represented by 2700 features
- recognition rate 98.91%
- open-set identification results was EER (FAR – FRR) = (1.58 % - 2.12 %) at threshold 0.750
Identification time on a personal computer (working frequency 2.40 GHz, 1066 MHz FSB and 8M cache) was 176 ms per person.

Future work

- 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.

- to investigate how the LDA applied on local Haralick features and local binary LDA influence the results of the identification.
Thank you for your attention!