Knuckle Biometrics for Human Identification

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Summary. In this paper we present human identification method based on knuckle biometrics also termed as FKP (finger-knuckle-print). Knuckle is a part of hand, and therefore, is easily accessible, invariant to emotions and other behavioral aspects (e.g. tiredness) and most importantly is rich in texture features which usually are very distinctive. The major contribution of this paper are texture-based knuckle features and their evaluation using IIT Delhi knuckle image database.

1 Introduction

Even though biometric identification systems became our reality and are no longer science-fiction visions, only several modalities have been widely deployed and such systems still have many drawbacks. The most known and often used modalities are fingerprints, face, hand geometry and iris. These are widely deployed in large-scale systems such as border control and biometric passports. But due to the problems with large-scale scalability, security, effectiveness and last but not least user-friendliness and social acceptance (e.g. even some governments protested vs. American policy of fingerprint enrollment for visitors) new emerging modalities are still needed.

Therefore, in this paper we present our approach to identify humans on the basis of their knuckles. Knuckle is a part of hand, and therefore, is easily accessible, invariant to emotions and other behavioral aspects (e.g. tiredness) and most importantly is rich in texture features which usually are very distinctive. Knuckle biometrics methods can be used in biometric systems for user-centric, contactless and unrestricted access control e.g. for medium-security access control or verification systems dedicated for mobile devices (e.g. smartphones and mobile telecommunication services).

Even though knuckle biometrics is relatively unknown and new modality, there already are some results and feature extraction methods. So called KnuckleCodes have been proposed and other well known feature extraction methods such as DCT , PCA, LDA, ICA, orientation phase, Gabor filters have been investigated showing very good identification results [1] [2] [3] [4] [5].

R.S. Choraś (Ed.): Image Processing & Communications Challenges 2, AISC 84, pp. 91–98.
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Hereby, we propose texture feature extraction methods such as Probabilistic Hough Transform (PHT) and Speeded Up Robust Features (SURF) and the original 3-step classification methodology.

The paper is structures as follows: in Section 2 general view on our system architecture is presented. In Section 3 knuckle image preprocessing is described. Feature extraction methods are proposed in Section 4. Classification methodology is presented in Section 5. Results and conclusions are given thereafter.

2 Knuckle Biometrics System Architecture Overview

The architecture of our knuckle biometrics system is presented in Fig 1.

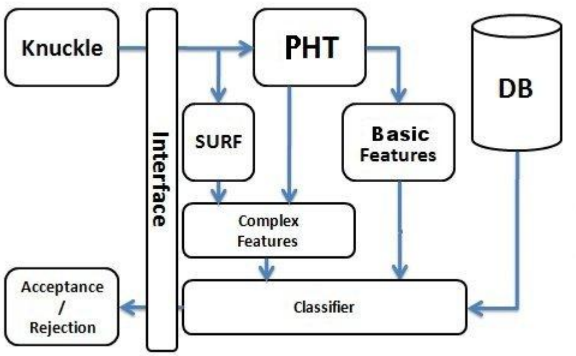

Fig. 1. Architecture of the proposed knuckle biometrics system

Firstly, the knuckle image is obtained from individual requesting access to the system. The knuckle image is preliminary processed to gain the characteristic features. The preprocessing includes both edge detection and thresholding. The image is further analyzed by means of Probabilistic Hough Transform (PHT), which is used both for determining the dominant orientation and also for building the basic feature vector. We also calculate enhanced feature vector using PHT output giving the input for final classifier which uses the SURF texture features.

Then the 3-step classification methodology is applied (in a broad-narrow manner). For computed "basic feature vector" nearest neighbors yielding the shortest Euclidean distance are chosen. For each image in kNN set the complex feature vectors are compared. The approach with kNN allows to decrease the complex computation without losing the overall system effectiveness (as discussed in details in section 6).

3 Knuckle Preprocessing Phase

The most noticeable knuckle texture features are the lines and wrinkles located on bending area of finger joints (see the first row in Fig. 3).

Therefore our methodology focuses on extracting these lines. First the image is binarized using an adaptive threshold estimated by means of equation 1:

$$T = \mu - \frac{\delta}{6}, \tag{1}$$

where T indicates the threshold value, μ the mean value and δ the standard deviation. Both the mean value and the standard deviation are computed locally in blocks of 7×7 pixels size.

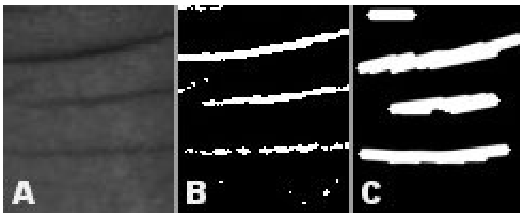

Fig. 2. The knuckle image example (A), enhanced major lines after thresholding (B), and the lines detected by PHT (C)

The result of adaptive thresholding can be seen in Fig. 2 B. It can noticed that such an image is quite noisy, since some edges suffer from line discontinuities while the background is filled with small spots. This problem is solved by adapting the Probabilistic Hough Transform (PHT). Later, the PHT also is used in our approach for extracting the dominant orientation and building the "basic feature vector".

4 Feature Extraction

4.1 Short Feature Vector (Basic Features)

The basic features vector describing the knuckle texture is built using the PHT output information, which contains set of line descriptors represented by formula 2, where $LD_i(N)$ stands for $N-th$ line descriptor of $i-th$ image, (b_x, b_y) the Cartesian coordinates of line starting point, (e_x, e_y) the Cartesian coordinates of line end point, θ the angle between the line normal and the X-axis, and d the particular line length expressed in pixels.

The number of extracted lines (N) depends strictly on knuckle spatial properties and varies, therefore these are not directly used to build feature vector.

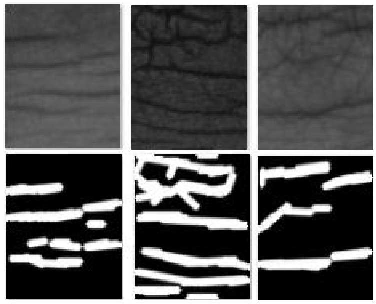

Fig. 3. Sample knuckle images and their representation after applying PHT transform

$$LD_i(N) = [b_{xN}, b_{yN}, e_{xN}, e_{yN}, \theta_N, d_N] \tag{2}$$

Due to the fact the particular knuckle may be rotated, the dominant orientation based on Hough transform is extracted using the θ angle from the line descriptors, which is used to rotate analyzed image in opposite direction to align the dominant line perpendicular to y-axis. After that the y position of particular line and its length is used to build the feature vector. The 30-bins 1D histogram is adapted.

The vectors described in this section were named "basic" since these are relatively short (one row vector of length 30) and are used for general data set clustering to decrease the number of computations and comparisons of complex features vector in further phases of our human identification system.

4.2 Knuckle Lines Model

The set of line descriptors (eq. 2) obtained from Hough transform are converted to image representation giving input for matching algorithm. Both query and template images (chosen from kNN selected by basic feature classifier) are transformed and compared using the Euclidean metric. The output of matching block is the scoring map, which is 30x30 of size. The size is determined by searching ranges. In this case the template image is offset in $< -15, 15 >$ range both on x and y dimension as is it defined by formula 3, where i and j are defines the element in scoring map, H and W defines query image width and height respectively, q and t represents query and template images respectively.

$$score(i, j) = \sum_{x=0}^{W} \sum_{y=0}^{H} (q(x, y) - t(x + i, y + j))^2 \tag{3}$$

The lowest score (the shortest distance) is selected giving the information about how the query image is similar to template, and allows to handle offsets in knuckle images. This is necessary since the knuckle database images are acquired using a peg-free method [6].

The 5 images from kNN set yielding the lowest score are chosen giving the input for SURF-based classifier.

4.3 Knuckle Texture Descriptors

The SURF stands for Speeded Up Robust Features and is robust image detector and descriptor. It was firstly presented by Herbert Bay in 2006 [9]. It is widely used in object recognition and 3D reconstruction. The key-point of the SURF detector is the determinant of the Hessian matrix, which is the matrix (eq. 4) of partial derivates of the luminance function.

$$\nabla^2 f(x,y) = \begin{bmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x \partial y} \\ \frac{\partial^2 f}{\partial x \partial y} & \frac{\partial^2 f}{\partial y^2} \end{bmatrix} \tag{4}$$

$$det(\nabla^2 f(x,y)) = \frac{\partial^2 f}{\partial x^2}\frac{\partial^2 f}{\partial y^2} - \left(\frac{\partial^2 f}{\partial x \partial y}\right)^2 \tag{5}$$

The value of the determinant (eq. 5) is used to classify the maxima or minima of the luminance function (second order derivative test). In the case of SURF the partial derivatives are calculated by convolution with the second order scale normalized Gaussian kernel. To make the convolution operation more efficient the Haar-like function are used.

If the determinant value is greater than threshold (estimated during experiments on learning data set) then it is considered as a fiducial point. The greater the threshold is the less points (but strong ones) are detected. For each of the fiducial points the texture descriptor is calculated.

In our approach we use the SURF points to find the closest matching (if any) between querying image and the templates selected by PHT-based classifier. Firstly the points yielding the Hessian determinant value greater than threshold are selected for both querying and the template images resulting in two points data set. Basing on texture descriptors the matching pairs between those sets are found and the outliers (points in one data set that do not

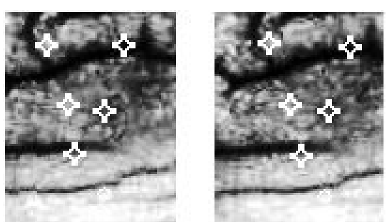

Fig. 4. Detected fiducial SURF points for queering image and its corresponding matches for the template image

have representative in the second data set) are removed. Then the matching cost between those sets is estimated using eq. 6:

$$m_{cost} = \sum_{i=0}^{N} d(p_i - \frac{1}{N}\sum_{j=0}^{N} p_j, q_i - \frac{1}{N}\sum_{j=0}^{N} q_j), \tag{6}$$

where N, d, p and q represents the number of matching pairs, Euclidean distance, point from template image and point from query image respectively. Example of such a mapping is shown in Fig. 4.

5 Classification

Hereby we propose classification methodology that consists of 3 consecutive steps: selecting 50 images on the basis of basic vector, then selecting 5 images on the basis of PHT feature vector, and finally SURF feature vector is used.

When basic feature vector for particular knuckle image is computed it is looked up in data base to find k nearest neighbors yielding the nearest Euclidean distance. The k number was determined empirically as an compromise of system effectiveness and system performance. Classification error is decreasing significantly when the number of neighbors (k) is increased. Basing on experiments we set these number to 50.

For each object form k nearest neighbors the PHT-based method is used to obtain 5 closest matching. For each of these images only one is chosen. In case the SURF-based classifier fails and is unable to find matching template then the first nearest neighbor obtained from PHT is returned with appropriate matching score.

6 Results

The proposed approach was tested using IIT Delhi Knuckle Database [6]. The knuckle images were obtained from 158 individuals. Each individual contributed five image samples which implies 790 images in database. The database was fully acquired over a period of 11 months.

For efficiency assessment the 5-fold method was applied (the same method as the authors of the database applied in [4]) and average of experiments results is presented. The average equal error rate obtained during experiments is 1.02%.

The table shown in Fig. 6 shows the EER deviation from its mean value and EER during each of experiments. The FAR and FRR vs system threshold for one of the experiments is shown in Fig. 5.

The experiments show that combination of PHT and SURF gives better results than each of this method used separately. The PHT gave 95.56% classification error while the SURF 85.75%. The SURF failed so often due to the fact it was unable to find matching between query knuckle image and the

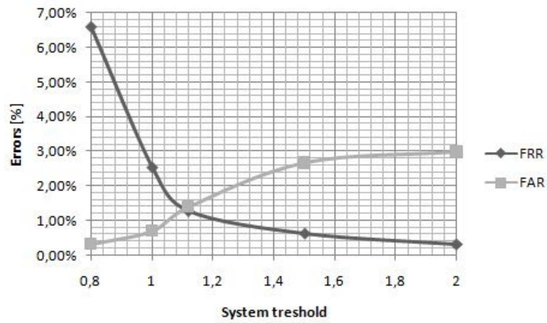

Fig. 5. FAR vs. FRR

Experiment	#1	#2	#3	#4	#5	AVG. EER
EER	0.32%	1.30%	0.95%	1.26%	1.26%	1.02%
					STD:	0.50%

Fig. 6. ERR obtained during experiments

template. Those fails were covered by PHT. However the PHT failed when it came to distinct two or more similar knuckles in k nearest neighbors. In this situation SURF was more accurate.

Obtained results suggest that using simple and fast line and texture extraction techniques is promising and may yield satisfactory results.

7 Conclusions

In this paper new developments in human identification based on knuckle texture features are presented. The major contribution of the paper are: new knuckle feature extraction methodology based on PHT (Probabilistic Hough Transform) and SURF features as well as original classification methodology. The reported results are very good and comparable (slightly better) to other methods (e.g. [4]). However, our methods are efficient and fast so that can be applied to contactless biometrics using mobile devices in the very near future [10].

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