A Short Overview of Feature Extractors for Knuckle Biometrics

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Abstract. In this paper an overview of image processing methods for feature extraction applied to knuckle biometrics also termed as FKP (finger-knuckle-print) is presented. 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. In this paper a short overview of the known recent approaches to human identification on the basis of knuckle images is given.

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. For example fingerprint and faces are widely deployed in large-scale systems such as border control, asylum control and biometric documents. But due to the problems with large-scale scalability, security, effectiveness and last but not least user-friendliness and social acceptance new emerging modalities are still investigated. One of such new and promising modalities is human knuckle.

In this paper the overview of feature extractors for such emerging modality, namely knuckle or finger-knuckle-print (FKP) is presented. 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

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control or verification systems dedicated for mobile devices (e.g. smartphones and mobile telecommunication services).

The sample knuckle image from IIT Delhi Database is presented in Figure 1 [1].

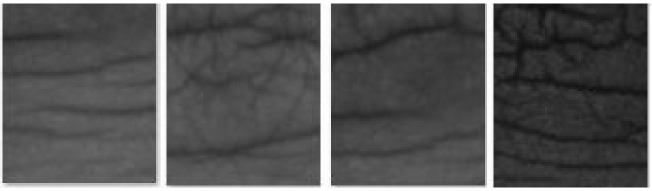

Fig. 1 Sample knuckle images from IIT Delhi Database [1]

2 Feature Extractors for Knuckle Biometrics

Most of the applied methods originate from known signal processing transformations or image processing methodologies. In general those can be categorized as approaches based on:

- Gabor-based approach (including e.g. 1D Log-Gabor),
- Ridgelets and transforms (Radon, Riesz),
- (Probabilistic) Hough transform (PHT),
- SIFT and SURF,
- Phase correlation functions.

2.1 Gabor-Based Features

It seems that Gabor based feature extraction is most common approach for knuckle biometrics. Of course in such approach (due to high dimensionality of Gabor filtering output) various dimensionality reduction techniques are also engaged.

The general function of the two-dimensional Gabor filter family can be represented as a Gaussian function modulated by a complex sinusoidal signal [2]. Specifically, a two-dimensional Gabor filter $\psi(x,y;\sigma,\lambda,\theta_k)$ can be formulated as:

$$\psi(x,y;\sigma,\lambda,\theta_k) = \exp\left(-\frac{x_{\theta_k}^2 + \gamma^2 y_{\theta_k}^2}{2\sigma^2}\right) \exp\left(\frac{2\pi x_{\theta_k}}{\lambda} i\right), \tag{1}$$

where $x_{\theta_k} = x\cos\theta_k + y\sin\theta_k$; $y_{\theta_k} = -x\sin\theta_k + y\cos\theta_k$; σ is the standard deviation of the Gaussian envelope along the x- and y-dimensions; γ is the spatial aspect ratio and; λ and θ_k are the wavelength and orientation, respectively [3] [4].

Foe example, Shariatmadar et al. [5] apply Gabor feature extraction followed by PCA and LDA for four fingers. Then feature level fusion is made before the matching process. Yang et al. [6] use Gabor filtering features and OLDA (Orthogonal LDA). Similarly, 8 Gabor filtering orientations and 5 scales are also used in FKP recognition based on Local Gabor Binary Patterns ([7]).

Meraoumia et al. [8] propose to use result of 1D Log-Gabor filtering in a palmprint and knuckle multimodal system. 1D Log-Gabor filters were also used by Cheng et al. [9] to calculate features of knuckle images in a contactless scenario (images acquired by smartphones).

Zhang et al. ([10]) proposed to use Gabor filters create so called competitive coding (CompCode) representations of knuckle images. Later they (Zhang et al. [11]) proposed Gabor filtering to create improved competitive coding (ImCompCode) and magnitude coding (MagCode) representations of knuckles. The same authors also proposed to use known Gabor characteristics to obtain ensemble of local and global features/information. They proposed an LGIC (local-global information combination) scheme basing on CompCode as well as Phase Only Correlation (POC) and Band Limited Phase Only Correlation [12].

It is worth to mention that global subspace methods such as PCA, LDA and ICA can be used not only for dimensionality reduction (of. e.g. Gabor filtration based vectors) but also as global appearance feature extractors as shown in [13].

2.2 (Probabilistic) Hough Transform

In [14] image is analyzed by means of Probabilistic Hough Transform (PHT), which is used both for determining the dominant orientation and also for building the intermediate feature vector. This feature 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.

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

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 calculated since the longest and characteristic lines of knuckles are concentrated around one rotation angle.

The vectors obtained by PHT 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

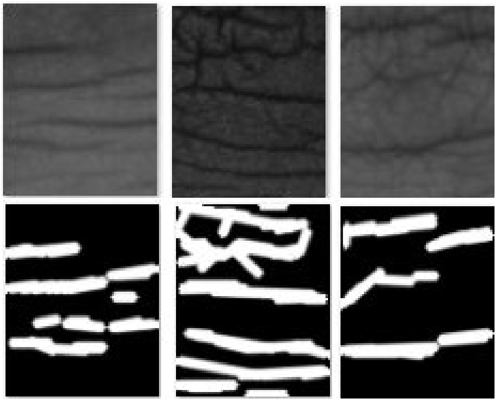

Fig. 2 Sample knuckle images and their representation after applying PHT transform

further phases of our human identification system. The set of line descriptors (eq. 2) obtained from Hough transform are then converted to image representation giving input for matching algorithm.

2.3 SIFT and SURF Feature Extractors

The SIFT stands for scale invariant feature transform. It is often used to extract salient points and is used in many applications such as biometrics or retrieval [15, 16]. SIFT features and their variations are based on image gradients of the pixels in a window around a salient point, and do not take color information into account. Therefore it was proposed as knuckle feature extractor in [17] and [18]. Authors used SIFT transform after enhancing the image, e.g. by Gabor filters.

The SURF stands for Speeded Up Robust Features and is robust image detector and descriptor. It was firstly presented by Herbert Bay in 2006 [19]. 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. 3) of partial derivates of the luminance function.

$$\nabla^2 f(x,y) = \begin{bmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x \partial y} \\ \frac{\partial^2 f}{\partial x \partial y} & \frac{\partial^2 f}{\partial y^2} \end{bmatrix} \tag{3}$$

$$det(\nabla^2 f(x,y)) = \frac{\partial^2 f}{\partial x^2}\frac{\partial^2 f}{\partial y^2} - \left(\frac{\partial^2 f}{\partial x \partial y}\right)^2 \tag{4}$$

The value of the determinant (eq. 4) 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 to represent the derivates.

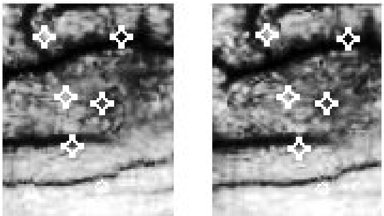

Fig. 3 Detected fiducial SURF points for queering image and its corresponding matches for the template image

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 [14] SURF points are used to find the closest matching (if any) between querying image and the templates selected by PHT-based classifier (used by authors in previous step to create intermediate vector (see section 2.2).

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 have representative in the second data set) are removed. Then the matching cost between those sets is estimated using eq. 5:

$$m_{cost} = \sum_{i=0}^{N} d(p_i - \frac{1}{N}\sum_{j=0}^{N} p_j, q_i - \frac{1}{N}\sum_{j=0}^{N} q_j), \tag{5}$$

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. 3.

Authors of [20] fused both extractors: SIFT and SURF, which allows to describe local patterns (of texture) around key characteristic points. Of course, the images are to be enhanced before feature extraction step.

2.4 Ridgelets and Transforms (Radon, Riesz)

Another approach to knuckle feature extraction is to use ridgelets or known signal processing transforms such as Radon Transform and Riesz Transform. Ridgelets are able to represent features of images with many lines such as knuckles. Ridgelets are based on Radon transform, in particular on FRAT (Finite Radon Transform). Wavelet transform is used to each projection of the Radon transform. Digital form of ridgelets applied on FRAT is called Finite Ridgelet Transform (FRIT).

Such approach was used in several papers by Goh et al., e.g. in both [21] and [22] in their proposition of bi-modal knuckle-palm biometric system (however, they proposed other feature extractors to palmprints).

In [23] Radon Transform was used, but in different manner. Authors proposed to apply Localized Radon Transform (LRT) for a discrete image to create so called KnuckleCodes which are later matched (similarly to FingerCodes and IrisCodes used for other modalities).

In a recent paper Zhang and Li ([24]) proposed to use Riesz transform to encode local characteristics of knuckle images. Authors successfully applied 1st order and 2nd order Riesz transforms to calculate so called RCode1 and RCode 2 and reported a very promising results. Both RCode1 and RCode2 were applied by authors to knuckle and palmprint images.

2.5 Phase Correlation Based Knuckle Similarity Matching

Another approach to represent local knuckle features is based on Phase Correlation Function (PCF) also termed as Phase Only Correlation (POC) [25] [26]. Phase correlation approach relies on Discrete Fourier Transform (DFT) and Inverse DFT and shows similarity between two transformed images.

In most realizations, in order to eliminate meaningless high frequency components (in classic PCF/POC all frequencies are involved), the Band-Limited Phase Only Correlation (BLPOC) is used [25]. In [27] PCF was used for both knuckle and palmprint in a bi-modal system.

3 Conclusions

Knuckle of finger-knuckle-print modality becomes an emerging trend in biometrics and computer vision communities. The major goal of this paper was to briefly present image processing based feature extractors applied to the task of human identification on the basis of knuckles. It was not author goal to compare, assess or evaluate the described approaches.

It is worth to note that most proposed methods and papers are rather recent which proves growing interest in knuckle biometrics.

Apart from applying various, mostly texture oriented methods, the current noticeable trends are also:

1. application of knuckles in multi-modal biometric systems, mainly with palmprint, hand features or hand veins [8] [21] [24] [28],

2. application of knuckles in contactless (touchless) scenarios, especially with images acquired by mobile phones [9] [21] [29].

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