Finger Knuckle Print Identification with Hierarchical Model of Local Gradient Features

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Abstract. In this paper we present new biologically inspired method for biometric human identification based on the knuckle finger print (FKP). 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 proposed method is based on the hierarchical feature extraction model. We also showed the results obtained for PolyU knuckle image database.

Keywords: Finger Knuckle Print, FKP, Biometry, Local Gradient Features.

1 Introduction

In this paper the new biologically inspired feature extraction method for 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. Requirements of users and stakeholders prove that biometric systems will soon have to be user-centric meaning requirements-free, friendly, accepted and mobile [1,2]. One of such emerging modalities satisfying those requirements is knuckle also termed as FKP (finger-knuckle-print). It has several advantages, such as: invariance to emotions and other behavioural aspects, high-textured region (experiments prove it to be that very distinctive), up to 5 distinctive biometrics samples per one hand, and it is easily accessible. 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) [3]. The samples of knuckles images (index and middle finger for left hand and middle finger for right hand respectively) from PolyU Database are presented in Fig. 1.

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),

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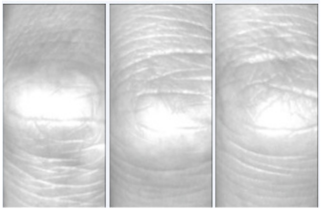

Fig. 1. Sample knuckle images from PolyU Database for one person (index and middle finger for left hand and middle finger for right hand)

Ridgelets and transforms (Radon, Riesz), (Probabilistic) Hough transform (PHT), SIFT and SURF as well as Phase correlation functions.

For example, Shariatmadar et al. [4] 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. [5] 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 [6]. Meraoumia et al. [7] propose to use result of 1D Log-Gabor filtering in a palmprint and knuckle multimodal system.

Later Zhang et al. [8] 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 [9].

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 [10]. In [11] 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. SIFT (scale invariant feature transform) was proposed as knuckle feature extractor in [12] and [13]. SURF stands for Speeded Up Robust Features and it was used in [11] find the closest matching (if any) between querying image and the knuckle templates. Authors of [14] 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.

Another approach to knuckle feature extraction is to use ridgelets or known signal processing transforms such as Radon Transform and Riesz Transform. Such approach was used in several papers by Goh et al., e.g. in both [15] and [16] in their proposition of bi-modal knuckle-palm biometric system (however, they proposed other feature extractors to palmprints).

Another approach to represent local knuckle features is based on Phase Correlation Function (PCF) also termed as Phase Only Correlation (POC) [17,18].

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 [17].

This paper is structured as follows. First, the proposed method overview is presented. Particularly it is explained how the original images are preliminary processed and how the information about relevant features are extracted and encoded. In the following section, the experiments and results are described. The conclusions are given thereafter.

2 Proposed Approach

The proposed approach follows the idea of HMAX model (see Fig.2) proposed by Riesenhuber and Poggio [19]. It exploits a hierarchical structure for the image processing and coding. The model is arranged in several layers that process information in a bottom-up manner. The lowest layer is fed with a grayscale image. The higher layers of the model are either called "S" or "C". These names correspond to simple the (S) and complex (C) cells discovered by Hubel and Wiesel [20].

In contrast to original model an additional layer that mimics the "retina codding" mechanism is added. Our previous experiments [24] showed that this step increases the robustness of the proposed method. This process is described in section 2.1.

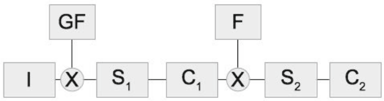

Fig. 2. The structure of a hierarchical model HMAX. (used symbols: I - image, S - simple cells, C - complex cells, GF - Gabor Filters, F - prototype features vectors, X - convolution operation).

The second modification includes a different method for calculating the S_1 layer response. The original model adapts the 2D Gabor filters computed for four orientations (horizontal, vertical, and two diagonal) at each possible position and scale. The Gabor filters are 11x11 in size, and are described by:

$$G(x,y) = e^{-(X^2+\gamma Y^2)/(2\sigma^2)} cos(\frac{2\pi}{\lambda}) \quad (1)$$

where $X = x\cos\phi - y\sin\phi$ and $Y = x\sin\phi + y\cos\phi$; x, y $\in< -5; 5 >$, and $\phi \in< 0; \pi >$. The aspect ratio (γ), effective width (σ), and wavelength (λ) are set to 0.3, 4.5 and 5.6 respectively. In this approach, the responses of 4 Gabor filters (two diagonals, horizontal and vertical) responses are approximated using Prewitt filters and voting algorithm described in section 2.2.The original HMAX model is intended to solve object detection problem with ability to preserve (to some extend) scale and transposition invariance. Therefore, two additional layers (S_2 and C_2) are introduced. In the case of PolyU dataset, the scale and transposition effects of biometric samples are so small, that can be suppressed by S_1. This is further explained in section 2.2. As a result, we replace these layers with classifier and use the C_1 layer responses as an input information.

2.1 Preprocessing Stage

In this work Difference of Gaussians (DoG) filter is used in preprocessing stage. It allows for feature enhancement and it involves the subtraction of two images blurred with different Gaussians filters (different standard deviation). It can be expressed with equation 2, where "$*$" represents convolution operation and σ_1 and σ_2 mentioned above standard deviations.

$$DoG_{\sigma_1\sigma_2}(x,y) = I * \frac{1}{\sigma_1\sqrt{2\pi}}e^{-\frac{x^2+y^2}{2\sigma_1^2}} - I * \frac{1}{\sigma_2\sqrt{2\pi}}e^{-\frac{x^2+y^2}{2\sigma_2^2}} \tag{2}$$

This preprocessing stage is intended to mimic the "retina coding" mechanism. Human retina shows remarkable and interesting properties of image enhancement. From a general point of view, the the retina serves as the first step of visual information processing. In the literature, there are several models explaining the basic mechanism the retina uses to encode visual information before it reaches visual cortex [22]. Basically, this model works as a filter that whitens the image spectrum and corrects luminance thanks to local adaptation. It has also the ability to filter out spatio-temporal noise and enhance the image details.

More simplistic approach to retina-based image enhancement was proposed in [23]. Authors adapted a local method that is based on a contrast equalisation. Within the sliding window authors normalised the luminance in the way, that the mean value is set to zero while the Euclidean norm is set to 1. This allowed to enhance image details and reduce the noise.

2.2 Gradient Information Coding

In our approach the S_1 layer covers whole knuckle sample image of WxH size. In this layer there are NxMx4 simple cells arranged in a grid of rectangular blocks. In each block there are 4 cells. Each cell is assigned a receptive field (pixels inside the block). Each cell is activated according depending on a stimuli. In this case there are four possible stimulus, namely vertical, horizontal, left diagonal, and right diagonal edges. As a result the S_1 simple cells layer output has dimensionality of a size 4 (x,y,scale and 4 cells). In order to compute responses of all four cells inside a given block (receptive field), an algorithm 1 is applied.

The algorithm computes the responses of all cells using only one iteration over the whole input image I. For each pixel at position (x, y) a vertical and horizontal gradients are computed (G_x and G_y). Given the pixel position (x, y) and gradient vector $[G_x, G_y]$ the algorithm indicates the block position (n, m) and type of cell (*active*) that response has to be incremented by magnitude $|G| = \sqrt{G_x^2 + G_y^2}$. In order to classify given gradient vector $[G_x, G_y]$ as horizontal, L,R-diagonal (left or right) or vertical the $get\_cell\_type(\cdot, \cdot)$ uses the wheel shown in Fig.3.

If a point $(|G_x|, |G_y|)$ is located between line $y = 0.3 \cdot x$ and $y = 3.3 \cdot x$ it is classified as a diagonal. If G_y is positive then the vector is classified as a right diagonal (otherwise it is a left diagonal). In case the point $(|G_x|, |G_y|)$ is located above line $y = 3.3 \cdot x$ the gradient vector is classified as vertical and as horizontal when it lies below line $y = 0.3 \cdot x$.

```
Data: Grayscaled image I of WxH size
Result: S_1 layer of size NxMx4
Assign G_min the low-threshold for gradient magnitude.
for each pixel (x, y) in image I do
    Compute horizontal G_x and vertical G_y gradients using Prewitt
    operator;
    Compute gradient magnitude |G| in point (x, y);
    if |G| < G_min then
        go to next pixel;

    else
        // Get cell type (horizontal, L,R-diagonal or vertical)
        active ← get_cell_type(G_x, G_y);
        // Calculate block indices
        n ← ⌊x · N/W⌋ ;
        m ← ⌊y · M/W⌋;
        // Increment response
        S_1[n, m, active] ← S_1[n, m, active] + |G_{x,y}|;
    end
end
```

Algorithm 1. Algorithm for calculating S_1 response

The C_1 complex layer response is computed using max-pooling filter, that is applied to S_1 layer.

3 Experiments and Results

The proposed approach was tested using PolyU Knuckle Database [25]. The knuckle images were obtained from 165 individuals. Each individual contributed 10-12 image samples per left index, left middle, right middle and right index finger.

For evaluation purposes we have adapted the stratified 10-fold cross-validation technique. For that approach the data obtained for learning and evaluation purposes is divided randomly into 10 parts (sets). For each part it is intended to preserve the proportions of labels in the full dataset. One part (10% of full dataset) is used for evaluation while the remaining 90% is used for training.

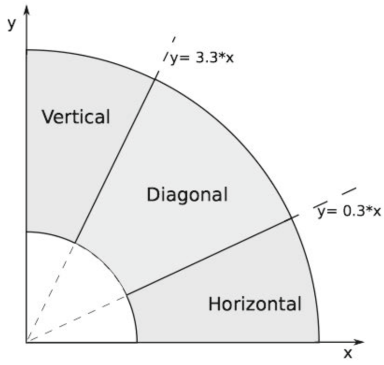

Fig. 3. A part of wheel that is used by $get\_cell\_type(\cdot, \cdot)$ to recognise a given gradient vector $[G_x, G_y]$ as horizontal, diagonal or vertical

When the classifier is learnt the evaluation data set is used to calculate the error rates. The whole procedure is repeated 10 times, so each time different part is used for evaluation and different part of data set is used for training. The result for all 10 runs (10-folds) are averaged to yield an overall error estimate.

For evaluation purposes we have used WEKA toolkit. In these experiments we evaluated different classifiers but kNN (where k=1), NaiveBayes, and RandomTrees gave comparable and promising results. The numbers of correctly and incorrectly classified instances are presented in Table 1.

Table 1. Effectiveness for PolyU Dataset

	Correctly Classified	Incorrectly Classified
kNN	**98.94%**	**1.06%**
NaiveBayes	95.81%	4.19%
50-RandomTrees	91.92%	8.08%
150-RandomTrees	96.87%	3.13%

In the Fig.4 the ROC curve for the kNN classifier is presented. The experiments showed that it is possible to achieve 0.9% of ERR (Equal Error Rate). However, the process of decreasing the False Acceptance Ratio causes rapid growth of False Rejection Ratio.

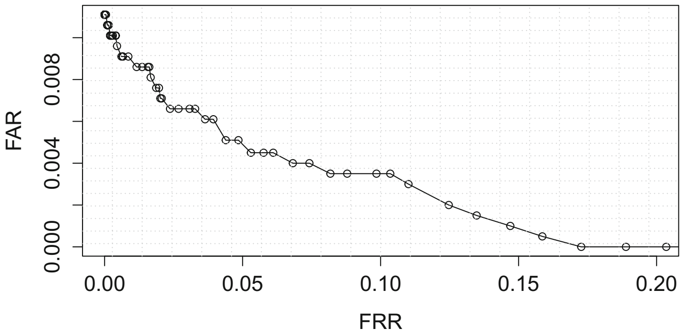

Fig. 4. FAR vs. FRR

4 Conclusions

In this paper new developments in human identification based on knuckle texture features are presented. The major contribution of the paper is the proposal of new biologically inspired knuckle feature extraction methodology based on hierarchical HMAX model. The method was evaluated using the benchmark PolyU database and we report the promising results.

In our opinion, the effectiveness of FKP based identification, should shortly allow for the application of knuckles in multi-modal biometric systems, mainly with palmprint, hand features or hand veins [7,15], as well as for application of knuckles in contactless (touchless) scenarios, especially with images acquired by mobile phones [15].

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