Fast Feature Extractors for Palmprint Biometrics

Michał Choraś and Rafał Kozik

Institute of Telecommunications,
University of Technology & Life Sciences
Bydgoszcz, Poland
{chorasm,rafal.kozik}@utp.edu.pl

Abstract. In this paper we propose to use fast feature extractors for contactless palmprint biometric system dedicated for mobile devices. We present texture feature extraction methods based on box functions, PCA and Matching Pursuit algorithm. Such methods should be effective and computationally robust to be deployable on mobile devices.

1 Introduction and Motivation

Nowadays, most hand and palmprint biometric systems are supervised and require contact with the acquisition device. Such situation contributes to negative opinion and lack of trust to biometric systems in the society. The goal of the biometrics community should be to design biometric systems that could work in a seamless way in the unconstrained environment. Another requirement is the "mobility" understood as the mobility of the subject, sensors and services (both embedded in mobile devices such as smartphones).

Currently, only few studies have been devoted to unsupervised, contactless palm images acquisition and hand pose invariance [1][2]. In [3] authors proposed a system that uses color and hand shape information for hand detection process. Authors also introduced a new approximated string matching techniques for biometric identification, obtaining promising EER lower than 1.2%. In [4] authors proposed sum-difference ordinal filters to extract discriminative features, which allow to verify the palmprint identity in less than 200ms, without losing the high accuracy. Such fast feature extraction algorithms are dedicated for smart phones and other mobile devices.

Hereby, we propose to use palmprint in the contactless biometric system for mobile devices (unsupervised, uncontrolled image acquisition by mobile cameras).

The main contribution of the research described in this paper is a fast method for palmprint feature extraction. The proposed features are based on approximated eigenpalms enhanced with gradient information (HOG features). Results obtained for our palmprint database of right hands images (1) are promising.

The paper is structured as follows: in Section 2 the general overview of the method is provided. In Section 3 the proposed method is described in detail. Results and conclusions are given thereafter.

N. Chaki and A. Cortesi (Eds.): CISIM 2011, CCIS 245, pp. 121–127, 2011.

Fig. 1. Examples of palmprint images acquired by mobile phone camera

2 General Overview of the Method

The palmprint feature extraction methodology, proposed in this paper, is a combination of two techniques used for image description. The first one, adapting box functions, aims at describing the low frequency features, while the second one, engaging gradient and directional histograms, focuses on high frequency features.

The general description of proposed combination is shown in Fig. 2

Firstly, the low frequency features are extracted, then K gradient images of K nearest neighbors are compared to gradient image of the palmprint. The closest match within the system threshold is chosen in order to accept or reject the particular user.

3 Three-valued Box Functions

The box functions (that build Haar-like features) can be adapted in mobile devices or cameras (eg. face detectors) because they are very efficient and computationally effective.

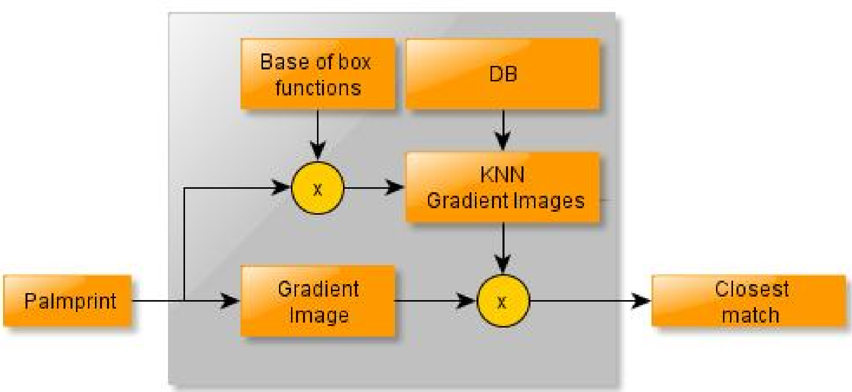

Fig. 2. Overview of the proposed method

The advantage of Haar-like features is that they can be efficiently computed in short and constant time at any scale or location thanks to the integral image (introduced by Viola and Jones in [5]).

However, in this paper, instead of Haar functions, two dimensional three-valued discrete functions are proposed to construct base of vectors:

$\{v_1, v_2, v_3, \ldots, v_N\}$

that will be used to project each of object image (p_k) onto new features space.

In other words, it is determined how much the particular object is similar to v_k (dot product a_{kn}).

The formula is described by equation 1:

$$a_{kn} = (p_k \cdot v_n). \tag{1}$$

The projection coefficients create the feature vector, that is described by equation 2:

$$w_k = (a_{k1}, a_{k2}, a_{k3}, \ldots, a_{KN}). \tag{2}$$

However, the key task is to find (faster than Ada-boost approach) efficient base of box functions than spans the feature space.

The technique proposed in this paper is PCA-guided.

3.1 PCA-Guided Feature Space Approximation

To represent feature space either non-orthogonal or orthogonal functions can be used. The most popular orthogonal basis used by computer vision algorithms are Walsh transform, DWT and PCA. Among these methods the PCA is the most widely and successfully used for palmprint and face recognition.

However, DWT, PCA and Walsh transforms are computationally expensive. The PCA could be even more expensive since it requires firstly to find eigenvectors set and then to compute palmprint projection onto this set.

Eigenvectors can be computed only once in offline mode (in order to decrease the mobile device burden). Nevertheless, the PCA projection is still computationally expensive since the dot product has to be computed (many floating point operations per one eigenvector).

Therefore we decided to represent the orthogonal PCA base with non-orthogonal base of box functions. Such approach allows to significantly reduce the number of multiplications without decreasing system effectiveness. For example the dot product of palmprint of size 512x512 and eigenpalm shown in Fig.5 requires 262144 multiplications. Using box functions (and integral images) this number can be reduced to 24 (4 read operations per one box as it is shown in Fig.6).

In the proposed method, the eigenvectors are first computed using original PCA. Each eigenvector is then normalized to have values within $< -1; 1 >$ range. Afterwards, each eigenvector is approximated by set of box functions that either can have -1,+1 or 0 sign. To solve the task of approximation, the Matching Pursuit algorithm is used.

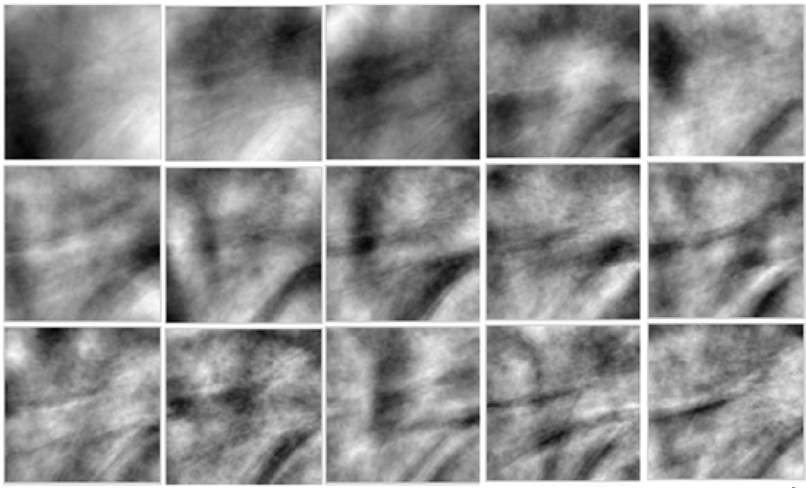

Fig. 3. Examples of eigenpalms

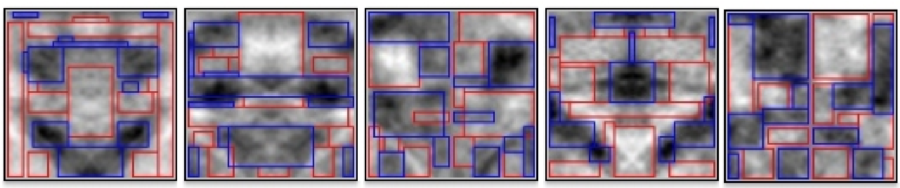

Fig. 4. Examples of eigenpalms approximated with box function (blue indicates -1, while red +1)

3.2 Matching Pursuit Algorithm for Palmprint Approximation

Matching Pursuit (MP) is a greedy algorithm that sequentially selects (in k steps) the base vector f from dictionary $D = \{f_1, f_2, ..., f_n\}$ (and adds it to the solution set $F_k = \{f_1, f_2, ..., f_k\}$), such that:

$$|c_i| = | < x - R_{F_{k-1}}(x), f_k > | \tag{3}$$

is maximized and $R_{F_k}(x) = \sum_{i=1}^{k} c_i f_i$ is an approximation of x after k steps. The example presenting one of the eigenvector and its approximation is shown in Fig. 5

3.3 Palmprint Gradient Descriptors

The method often used for gradient description is commonly known as HOG (Histograms of Oriented Gradients) descriptors. In this paper 9-bin histograms are used (20 degrees for each bin).

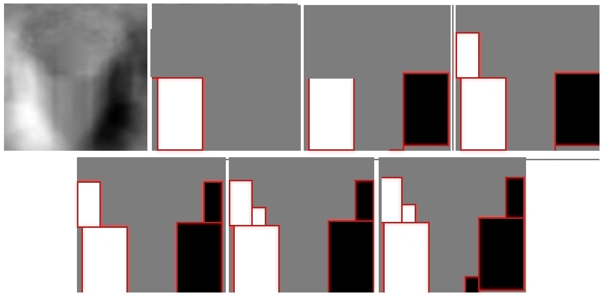

Fig. 5. One of the eigenvectors and its approximation at each iteration of MP algorithm

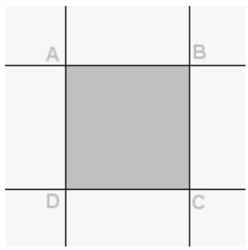

Fig. 6. When using integral images, computing average gradient magnitude for ABCD region of any size requires only 4 access operations

The palmprint image is initially divided into grid. In our case the grid of size 10x10 is used. For each grid cell HOG descriptor is computed. Each descriptor is a vector of length 9. Each vector component describes average magnitude of gradient for particular direction.

In order to speed-up the computations, the integral images are used to compute average magnitude for particular direction. The 9-bin histogram requires 9 integral images. Each integral image aggregates gradient magnitude for one direction.

The x and y components of the gradient are extracted as difference of luminance of two neighboring pixels. The direction of gradient is computed as $\arctan \frac{y}{x}$.

In order to compute average magnitude for block of texture (as it is shown in Fig.6) it is required to read only 4 values from integral image.

4 Results

We used our own database consisting of 252 images (there are 84 individuals, for each individual there are 3 images of the right hand) for testing method effectiveness. Standard mobile devices have been used (Canon, HTC, Motorola) and the resolution of images is 640x480.

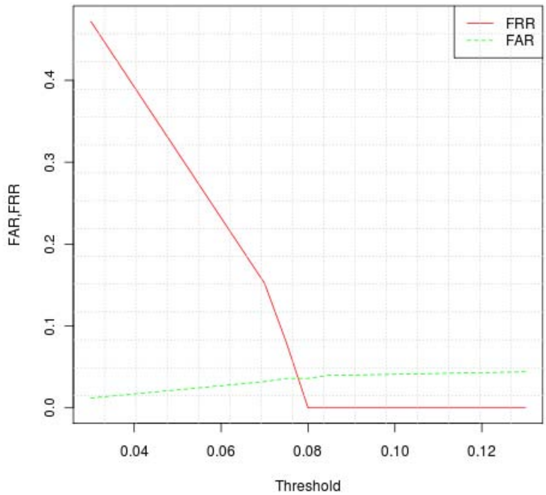

Fig. 7. FRR and FAR versus threshold for box function

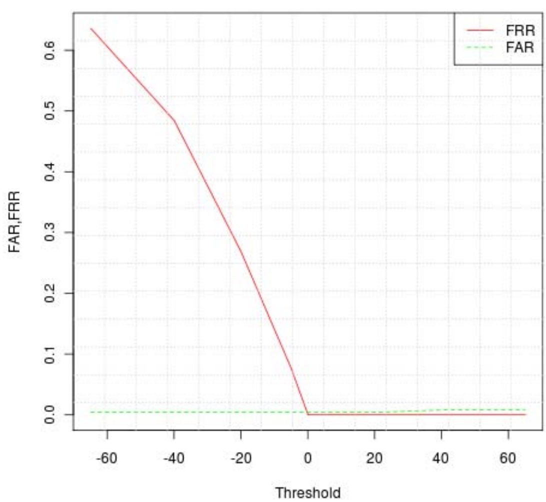

Fig. 8. FRR and FAR versus threshold for box function enhanced by HOG features

During the test classical 10-fold approach was used in order to assess the proposed method effectiveness.

Firstly, we evaluated the effectiveness of palmprint recognition based on box functions, then we assessed how gradient information can increase the effectiveness.

The effectiveness of palmprint recognition based on approximated PCA vectors is shown in Fig. 7. The average Equal Error Rate achieved for this method is 3.6%.

The results for features vector enhanced by HOG features are presented in Fig. 8. The average EER is equal to 0.4%.

5 Conclusions

In this paper our developments in palmprint feature extraction for human identification in biometrics system are presented.

We showed that palmprint texture features may be considered as very promising biometrics modality which can be used in contactless human identification systems. Our goal was to propose efficient feature extractors that can be run on mobile devices.

References

1. Fratric, I., Ribaric, S.: Real-Time Model-Based Hand Localization for Unsupervised Palmar Image Acquisition. In: Tistarelli, M., Nixon, M.S. (eds.) ICB 2009. LNCS, vol. 5558, pp. 1280–1289. Springer, Heidelberg (2009)
2. Methani, C., Namboodiri, A.M.: Pose Invariant Palmprint Recognition. In: Tistarelli, M., Nixon, M.S. (eds.) ICB 2009. LNCS, vol. 5558, pp. 577–586. Springer, Heidelberg (2009)
3. Doublet, J., Lepetit, O., Revenu, M.: Contact less palmprint authentication using circular Gabor filter and approximated string matching. In: Proc. of Signal and Image Processing (SIP), Honolulu, United States (2007)
4. Han, Y., Tan, T., Sun, Z., Hao, Y.: Embedded Palmprint Recognition System on Mobile Devices. In: Lee, S.-W., Li, S.Z. (eds.) ICB 2007. LNCS, vol. 4642, pp. 1184–1193. Springer, Heidelberg (2007)
5. Viola, P., Jones, M.: Rapid object detection using a boosted cascade of simple features. In: Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR 2001, vol. 1, pp. 511–518 (2001)
6. Choraś, M.: Novel techniques applied to biometric human identification. Electronics 3/2009 (March 2009)
7. Choraś, M.: Emerging Methods of Biometrics Human Identification. In: Proc. of 2nd International Conference on Innovative Computing, Information and Control (ICICIC 2007), p. 365. IEEE CS Press, Kumamoto (2007)
8. Kozik, R., Choraś, M.: Combined Shape and Texture Information for Palmprint Biometrics. Journal of Information Assurance and Security 5(1), 58–63 (2010)
9. Bay, H., Tuytelaars, T., Van Gool, L.: SURF: Speeded Up Robust Features. In: Leonardis, A., Bischof, H., Pinz, A. (eds.) ECCV 2006. LNCS, vol. 3951, pp. 404–417. Springer, Heidelberg (2006)