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HIGH PERFORMANCE SET OF FEATURES FOR BIOMETRIC DATA

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Abstract: *This paper focuses on the use of image-based techniques in biometric verification. A detailed review of the existing literature on texture descriptors is provided and several methods are compared on three well known biometric problems: palm verification, knuckle verification and fingerprint verification. The texture descriptors evaluated in this study are based on the most commonly used measures, i.e., Gabor filter bank response, local binary patterns, histogram of gradients, and local phase quantization. Moreover, different distance measures are compared for obtaining the best performing system. The most common method for handling biometric data is to determine a common set of optimal features and then apply standard machine-learning algorithms and distance measures to classify them. In this paper we use advanced supervised selection methods for determining an optimized set of features for training an ensemble of classifiers and for reducing the dimensionality of the feature set by discarding the less discriminative features. The optimization process requires that we first run several experiments to determine which feature set offers the most information. The best performing feature set is then combined and used in the ensemble classification. Extensive experiments conducted over the three well-known biometric datasets show that it is possible to find a set of descriptors that works well for all the three tasks. We are thus able to produce a set of optimal generalized features. The best tested method is local phase quantization.*

Keywords: *Texture Descriptors; Gabor Filters; Local Binary Patterns; Local Phase Quantization; Biometric Data.*

1. INTRODUCTION

This century biometric recognition has increasingly become one of the most widely studied pattern recognition problems. The field is being driven in large part by the increasing need of advancing technological systems, such as the Internet and cellular phones, to secure personal identification. It is not enough anymore to base identification on something the user knows. Passwords, secret codes, personal identification numbers (PINs), and answers to personal questions are unsafe and not user-friendly. These forms of identification can easily be forgotten, compromised, shared, or observed. Basing identification on biometrics, or on various intrinsic aspects of human being that are simultaneously unique to each individual, such as palm and fingerprints, is a viable solution to the growing need of tighter security.

Biometrics is the science of measuring and compiling distinguishing physical or biological features about an individual, such as facial structure, fingerprints, and the iris. Biometric recognition is defined by several critical issues involved in the problem, such as quality checking, aliveness detection, and multimodal authentication. Regardless of the biometric chosen, all recognition systems must isolate and extract a set of features in the biometric image or pattern that offers the greatest amount of information. Over the last decade, several methods have been developed for extracting features from an image and for classifying them. Texture-based methods, especially those using Local Binary Patterns (LBP) [1][2][4][5] and methods based on Gabor filters [6], are commonly employed in many biometric image classification, verification, and identification systems and form the focus of much current research.

Despite the fact that researchers have access to a large amount of biometric data, most texture-based methods have been tested and compared only on one or two datasets, generally representing the same biometric trait. An examination of the literature shows that different methods perform optimally on different datasets. The aim of this work is to find a generalized method, or an ensemble of methods, that works well across a number of different biometric problems. We accomplish this goal by examining several feature extraction approaches for representing images, and we propose a reliable method based on an ensemble where different feature descriptors are combined into an optimal general system. In developing our method, more than ten different texture descriptors are compared using three different biometric traits.

The remainder of this paper is organized as follows. In section 2 we discuss related research in texture-based methods for biometric verification using the biometric traits examined in this study. In section 3 we introduce the feature extraction methods studied in this work. In section 4 we describe the datasets and the testing protocol used in this work. In section 5 we explain the classification system proposed in this work. Section 6 reports experimental results obtained using our system on three different biometric traits.

Finally, in section 7 we draw some conclusions and discuss directions for future research.

2. RELATED WORK

In this section we review techniques for classifying the biometrics explored in this study: palm verification, knuckle verification, and fingerprint verification.

2.1. Palm Verification

Palm verification is an emerging biometric study typically based on the acquisition of a hand image using the digital camera and on the comparison of the palmprint impression. The different descriptors used in palm verification can be divided into the following three categories according to the types of information that they extract [8]:

1. Texture-based approaches, e.g., Gabor Filters [9][10], Discrete Cosine Coefficients [11], and Wavelets [12];
2. Line-based approaches, e.g., Line matching [13] and Line detection [14];
3. Appearance-based approaches, e.g., FisherPalm [15], EigenPalm [16], and 2DPCA [17].

A major bottleneck in performance is the use of a single descriptor. A number of papers in the literature show that an ideal Palmprint verification system should be based on the fusion of several descriptors [8][18][19][20]. As an example, in [8], the authors combine Gabor filters, Line detectors, and principal component analysis (PCA). The fusion is then performed at the score level.

In [20] an ensemble of classifiers is built from a Palm image by extracting five subimages. From each of these new images, five different feature vectors are extracted, one for each of the three feature extraction methods tested in that paper. The final score is then obtained by combining the scores of these different Palmprint representations.

2.2. Knuckle Verification

Using the entire finger as a biometric characteristic is a recent development in biometric pattern recognition, see e.g., [21][22]. Thus far both inner and outer knuckle prints have been studied. It is shown in [21] that the lines in the inner skin of the knuckle of the finger can be considered a viable biometric marker. In [22] an image-based finger matcher is proposed where the finger image is projected onto a lower-dimensional space using Principal Component Analysis. In [25] a new method for line feature knuckleprint matching is proposed, and in [23] the authors select a subset of Gabor filters using the entire image.

A recent method [24] uses the outer finger-knuckle-print, which refers to the inherent patterns of the outer surface around the phalangeal joint of the finger. In that study a novel Gabor based feature extractor was employed.

2.3. Fingerprint Verification

Fingerprint verification is probably the most known form of biometrics used to identify an individual and verify their identity. Among various approaches proposed in the literature for automated fingerprint verification, we are interested in image-based ones which base the comparison on the basic fingerprint patterns and thus requires that the images are aligned in the same orientation, By considering the different techniques that have been developed for aligning two fingerprints and the matching step, the image-based matchers can be divided in four main categories (for a survey read [26][36]):

- *Core alignment* is a method where each fingerprint is aligned to the template considering a reference point, usually the core point. A very well known example of this class is the FingerCode proposed by Jain et al. [27] that is based on the application of Gabor filters in the area around the core point. An improvement of FingerCode is proposed in [30] where different matching functions are tested for improving the performance of the original FingerCode. Some other methods in this category include those proposed in [29] and [31]. Theoh et al., [29] develop a method based on Fourier–Mellin descriptors extracted from a wavelet transformed image, and Zegarra et al. [31] compare several different wavelet descriptors and show that the Gabor wavelet achieves the best performance.
- *Minutiae alignment (*also called *hybrid alignment* in the literature [34][28]) is a method where the two fingerprints are aligned considering their minutiae sets. Ross et al. [28], using Gabor filters applied on a square grid, show that the minutiae-based alignment is more robust than the alignment based on the core point. Nanni and Lumini have proposed using Gabor filtering applied to different wavelet sub-bands in [33] and invariant locally binary patterns (LBP) in [35] and [36]. In [35] the fusion of the different descriptors (LBP and Gabor) is examined, and in [34], the Gabor filters are convolved starting from the minutiae localizations and orientations.
- *Core alignment and classification* is a method where all the fingerprints are aligned using a single reference point. The matching step can employ a machine learning classifier trained to distinguish between couples of matching and non-matching fingerprints [42].
- *Minutiae alignment and classification* is a method where the minutiae alignment only allows a pairwise alignment. This makes possible the extraction of a set of features from each couple of fingerprints to be mated that can be train with a two-class machine learning classifier that distinguishes between the

genuine and the impostor. For example, in [32] 17 features are extracted among which only few are image-based.

3. TEXTURE DESCRIPTORS

Biometric verification is a difficult machine classification problem that is best handled by combining multiple descriptors to boost performance. Good descriptors are invariant to image rotation and scale. In addition, they are robust in terms of variations in illumination.

The remainder of this section describes several texture descriptors examined in our proposed ensemble methods.

3.1. Invariant Local Binary Patterns

The Local Binary Pattern (**LBP**) [1] is a histogram that is based on a statistical operator calculated by examining the joint distribution of gray scale values of a circularly symmetric neighbor set of P pixels around a pixel $\mathbf{x}$ on a circle of radius R. The difference between the gray value of a pixel $\mathbf{x}$ from the gray values in one of its neighborhood u assumes: 1 if $u \geq x$; else 0. In this study, we use a multi-resolution descriptor that is obtained by concatenating three histograms calculated with the following parameters: (P = 8; R = 1) and (P = 16; R = 2).

A rotation invariant image descriptor based on uniform LPB is proposed in [40], where the discrete Fourier transform extracts a class of features that are invariant to the rotation of the input image starting from the histogram rows of the uniform patterns. These descriptors are known as the Local Binary Pattern Histogram Fourier (LBP-HF) features [40].

3.2. Local Ternary Patterns

A generalization of LBP is the Local Ternary Pattern (LTP) [4]. LTP represents the gray-scale differences between pixels using a ternary rather than a binary value. The difference between the gray value of a pixel x from the gray values in one of its neighborhood u assumes the three values by applying a threshold t: 1 if $u \geq x + \tau$; –1 if $u \leq \boldsymbol{x} - t$; else 0. LTP is a more discriminant descriptor and is less sensitive to noise. To reduce computational complexity, the ternary pattern is split into two binary patterns by considering the positive and negative components. The histograms computed from these two patterns are then concatenated. In this study we use (P=8; R=1) and (P=16; R=2), the feature vector is given by the concatenation of these two histograms. In this work two implementation of LTP are tested: a LTP variant where the uniform bins are considered (LTPu) and a variant where the rotation invariant bins are considered (LTPri). The interested reader can see [1] for more details on uniform bins and rotation invariant bins.

3.3. Gabor Filters

The 2D Gabor function has been widely used for fingerprint analysis, as well as other vision problems, since it optimally captures both local orientation and frequency information from a fingerprint image. The 2D Gabor function is a harmonic oscillator within a Gaussian envelope that is composed of a sinusoidal plane wave of a particular frequency and orientation. By tuning a Gabor function to specific frequency and direction, the local frequency and orientation information from an image can be obtained. A symmetric Gabor filter has the following general form in the spatial domain:

$$G(x, y; \nu, \sigma, \theta) = \exp\left(-\frac{x'^2 + y'^2}{2\sigma^2}\right) \cdot \cos\left(2\pi\nu x'\right)$$

$$x' = x \sin\theta + y \cos\theta$$

$$y' = x \cos\theta - y \sin\theta$$

where n is the frequency of the sinusoidal wave, q is the orientation and s is the standard deviation of the Gaussian envelope.

A filter bank usually consists of Gabor filters with various scales and rotations. The filters are convolved with the signal, resulting in a Gabor space. The filters in this study are obtained considering four scales as well as the following four angles for each scale: θ = 0°, 45°, 90°, 135°.

We also explore Log-Gabor filters [45], which are a logarithmic transformation of the Gabor domain that eliminates the annoying DC-component allocated in medium and high-pass filters.

We reduce our examination to those approaches that produce the best results:

- *TwoL [43]*: It divides each image into subwindows that are then divided into four subimages. The feature vector is given by the difference standard deviations of the Gabor images extracted from the subwindows of the different levels.
- *GaborB:* The standard deviation of the convolved image is used for the features.
- *Com (competitive code approach) [46]:* For each pixel of the image, the orientation information is extracted and represented as an "orientation code."
- *Imp (improved competitive code approach) [24]:* with a bank of Gabor filters, the orientation feature at each pixel is extracted. This is an improvement with respect to the competitive code in that the pixels lying on relatively ''plane'' areas (i.e., those pixels that do not reside on any lines and consequently do not have a dominate orientation) are removed from the orientation coding.
- *LogImp:* This is similar to Imp but the Log Gabor filters are used.
- *BOCV [47]:* This is a recently proposed method for palmprint recognition that tends to represent multiple orientations for a local region. The threshold for the binarization used in BOCV is set o

0 in the experiments reported in this paper (see [47] for details).

- *LogBCV:* This is similar to **BOCV** but the Log Gabor filters are used.
- *LGP [44]:* This is a recent method for encoding the local neighborhood variations of the Gabor phase at each orientation and scale.

3.4. Histogram of Gradients

The histogram of oriented gradients (**HoG**) [37] represents an image by a set of local histograms that count occurrences of gradient orientation in a local cell of the image. The implementation of the HoG is achieved by computing the gradients of the image, followed by dividing the image into small subregions, where a histogram of gradient directions is built for each subregion. The histograms are then normalized within some groups of the subregions, called blocks, to achieve better invariance to illumination changes.

In this study we use weighted HoGs as implemented in [38], where the subregions are obtained by dividing each image cell into $W \times W$ equal non-overlapping regions. The orientation and magnitude of each pixel is then calculated for each subregion. The absolute orientations are discretized over 9 equally sized bins in the 0° – 180° range. The resulting 9-bin histogram is calculated by weighing each pixel by the magnitude of its orientation according to the histogram bin.

3.5. Local Phase Quantization

Originally the Local Phase Quantization operator was proposed as a texture descriptor by Ojansivu and Heikkila [39]. Local phase quantization (LPQ) is a method that is based on the blur invariance property of the Fourier phase spectrum. LPQ uses the local phase information extracted from the 2-D short-term Fourier transform computed over a rectangular neighborhood at each pixel position of the image. Only four complex coefficients are considered, corresponding to 2-D frequencies. For more mathematical details refer to [39]. In this study we use the original code shared with us by the inventors of LPQ.

4. DATASETS AND PROTOCOLS

Our method is tested on the following benchmark datasets: Fingerprints and Palm & Knuckle. Some sample images are shown in Figure 1.

Fingerprints: Our experiments are conducted using the DB2 fingerprint database from FVC2002 [26]. This dataset contains 800 images from 100 individuals. According to the FVC2002 testing protocol, the following matching attempts are performed:

- *Genuine Recognition Attempts*: The template of each impression is matched against the remaining impressions of the same individual, but avoiding symmetric matches;
- *Impostor Recognition Attempts*: The template of the first impression is matched against the first impression of the remaining individuals, but avoiding symmetric matches.

In order to apply an image-based method the fingerprints are first aligned using their minutiae sets as in [2].

Palm & **Knuckle:** The experiments in this study utilize inkless hand images obtained from a digital Camera [24]. The database contains 7 samples from each user, for 100 users. For the knuckle verification problem, we report results obtained using only the middle-finger which are extracted as in [23]. The palm images are extracted as in [20]. For these two dataset, we use the same FVC2002 testing protocol described above.

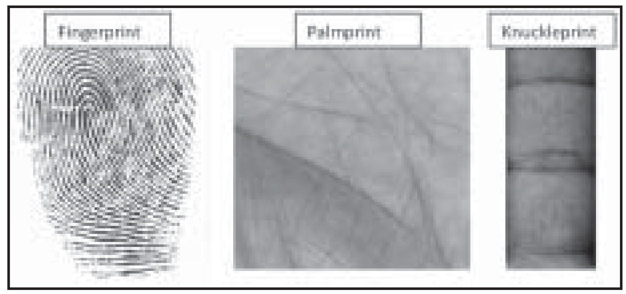

Figure 1: Samples from the Datasets

5. PROPOSED APPROACH

The same classification approach have been used in all the three datasets, based on the following steps: enhancement, image alignment, tessellation by a square overlapping grid and feature extraction, feature selection (only in the training phase), matching with a set of distances (one for each selected feature vector) combined by the sum rule.

Enhancement is performed using a method based on Fourier domain block-wise contextual filters,[1] as in [36] for fingerprint verification. In the palm and knuckle problem, preprocessing is performed as in [41].

Before the feature extraction, each image is first decomposed into overlapping square cells of fixed dimension *dim*×*dim* (the following values are used in this study: *dim* = 25 and *overlap* = 50%). Moreover, as in other papers [2][6] that couple LBP descriptors with various preprocessing methods in order to improve the classification performance, we perform a further preprocessing step before extracting *LBP* based and *HoG* features: such texture descriptors are calculated after convolving the images with the Gabor filters. The Gabor filters used in this study are obtained considering four scales as well as the following four angles for each scale: θ = 0°, 45°, 90°, 135°. For each convolved image a different distance is calculated, then the final distance is given by the sum of these 16 distances.

[1]http://www.cubs.buffalo.edu/resources/enchancement.zip

The feature selection step is performed according to sequential forward floating selection (SFFS),[2] a bottom up search procedure introduced by Pudil et al. [7]. It consists of a forward step followed by a conditional backward step. The forward step starts from an initially empty set of features and successively adds descriptors from a set of original candidates in order to optimize a given objective function. Each time a single descriptor is added, a backward step is performed that identifies the least significant descriptor in the current feature set and removes it unless it is the last descriptor added.

The backward step is repeated according to the significance of the least significant descriptor in the current set as compared to previous sets of the same cardinality. We adopt as the objective function the minimization of the equal error rate (EER).

The matching value between two images is calculated by a distance function. We test several distances[3] between the feature vectors x_r and x_s related to the unknown iamge and the template respectively. We obtain the best performance with the following distances:

- City block metric (CB) :

$$dist_{CB}(x_r, x_s) = \sum_{j=1}^{n} \left| x_r(j) - x_s(j) \right|$$

- Cosine distance (CD), i.e., one minus the cosine of the included angle between points (treated as vectors)

$$dist_{CD}(x_r, x_s) = (1 - x_q, x_s^{'}) / (x_r^{'} x_r)^{0.5} (x_s^{'} x_s)^{0.5}$$

- Hamming distance (HD), i.e., the number of positions at which the corresponding symbols are different.

Notice that when more descriptors are combined, the distances related to each descriptor are normalized to mean 0 and standard deviation 1. Finally, these similarities are combined by sum rule.

6. EXPERIMENTAL RESULTS

The performance has been measured by means of the well known Equal Error Rate (EER) [26]. The EER is a unique measure for characterizing the security level of a biometric system. It is the error rate when the frequency of fraudulent accesses (False Match Rate, FMR) and the frequency of rejections of people who should be correctly verified (False Non-Match Rate, FNMR) assume the same value.

In table 1 we compare the performance of the different approaches explored in this paper: for each descriptor the EER obtained using by the best distance function among the three datasets (reported the column *Distance* of the table 1) is shown.

[2] It is implemented as in PRTools 3.1.7 Matlab Toolbox

[3] All the methods available in the pdist function of MATLAB

Table 1
Comparison among the Approaches Based on Different Descriptors

Descriptor	*Distance*	*Dataset*		
		Palm	*Knuckle*	*Fingerprint*
TwoL	CD	17.4	23.4	6.7
GaborB	CD	10.9	10.7	4.3
Com	HD	8.8	9.6	25.8
Imp	HD	9.1	10.5	23.3
LogImp	HD	21.1	15.8	10.5
BOCV	HD	8.6	8.1	38.2
LogBCV	HD	16.7	16.5	38.1
LGP	HD	13.6	16.3	6.5
LTPu	CB	7.5	7.8	4.2
LTPri	CB	9.8	10.1	4.2
LBP-HF	CB	8.1	8.4	3.7
LPQ	CB	6.5	7.3	3.3
HoG	CB	11.3	9.9	4.1

It is interesting to note the huge performance difference among the different datasets. In our implementation, BOCV works very well in Palm & Knuckle but it obtains a very high EER in the Fingerprint verification. This is due to the differences among the different biometric traits.

Moreover, note that in several works (e.g., [24]), the problem of reducing displacement in the image alignment was addressed by translating one set of features in the horizontal and the vertical directions several times, and the minimum of the resulting matching distances was considered to be the final matching distance. Since our aim is a comparison of texture descriptors, only the extracted images are compared for simplicity.

We want to stress the performance of LPQ, a very recent descriptor [39]: it obtains the best performance across all the tested problems.

Table 2
Comparison among the Fusion Approaches

Ensemble	*Dataset*		
	Palm	*Knuckle*	*Fingerprint*
IN	5.8	6.5	2.1
OUT	6.2	8.1	5.6
ALL	6.1	7.5	2.4
SA	6.5	7.3	3.3

In table 2 we report the results obtained combing several texture descriptors:

- IN, where the descriptors are selected separately in each dataset. It can be considered as the upper bound performance. The number of retained features is different in each dataset, it is chosen for minimizing the EER in the dataset;

- OUT, where the descriptors used in a dataset are selected in the other two datasets;
- ALL, which is the best average fusion for all three dataset, i.e., it combines **LPQ**, **LGP**, and **LBP-HF**.
- SA, reports the performance of the best stand-alone approach (based on LPQ).

The best set of descriptors is given by the combination of LPQ, LGP and LBP-HF. This combination obtains performance only slightly lower than that obtained when the descriptors are selected separately in each dataset. The good performance of this combination is not surprising since each method extracts different information.

7. CONCLUSION AND DISCUSSION

This paper focused on the study of texture descriptors in biometric verification. Based on an analysis of prior research, we propose a set of descriptors that works well in three different problems, and we test for the first time different texture descriptors in the following problems: palm verification; knuckle verification; and fingerprint verification.

The descriptors explored in this paper are based on the most used measures: Gabor filters based descriptors, local binary patterns based descriptors, histogram of gradients, and local phase quantization.

The best performing descriptor is LPQ. It performed best across all tested datasets. This is the first time that LPQ is tested in these three problems, and our experiments demonstrate the value of this descriptor.

The best set of descriptors is given by combining LPQ, LGP, and LBP-HF. That this combination performs well is expected since each method extracts different information from the images.

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REFERENCES

[1] T. Ojala, M. Pietikainen, T. Maeenpaa, "Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns", *IEEE TPAMI*, **24 (7)**, 971-987, July-2002.

[2] L. Nanni, A. Lumini, "Local Binary Patterns for a Hybrid Fingerprint Matcher", *Pattern Recognition (2008)*, doi:10.1016/j.patcog.2008.05.013.

[3] Fröba, B., Ernst, A., 2004, "Face Detection with the Modified Census Transform", *In: Proc. 6th Int. Conf. on Face and Gesture Recognition – FG 2004*, 91-96, Seoul, Korea, May 2004.

[4] X. Tan and B. Triggs, "Enhanced Local Texture Feature Sets for Face Recognition under Difficult Lighting Conditions", *In Analysis and Modelling of Faces and Gestures*, Volume 4778 of LNCS, Pages 168-182. Springer, 2007.

[5] Liao S. and Chung A.C.S., "Face Recognition by Using Elongated Local Binary Patterns with Average Maximum Distance Gradient Magnitude", *Computer Vision – ACCV 2007*, 672-679.

[6] Goh Kah Ong Michael, Tee Connie, Andrew Beng Jin Teoh, "Touch-less Palm Print Biometrics: Novel Design and Implementation", *Image and Vision Computing*, to Appear 2008.

[7] P. Pudil, J. Novovicova, J. Kittler, "Floating Search Methods in Feature Selection", *Pattern Recognition Letters*, **15 (11)**, (November-1994) 1119-1125.

[8] A. Kumar, D. Zhang, "Personal Authentication using Multiple Palmprint Representation Pattern Recognition", **38**, 2005, 1695–1704.

[9] D. Zhang, W.K. Kong, J. You, M. Wong, "On-line Palmprint Identification", *IEEE Trans. Patt. Anal. Mach. Intell.*, **25**, 2003, 1041–1050.

[10] W.K. Kong, D. Zhang, W. Li, "Palmprint Feature Extraction using 2-D Gabor Filters", *Patt. Recog.*, **36**, 2003, 2339–2317.

[11] A. Kumar, D. Zhang, "Integrating Shape and Texture for Hand Verification, in: Proceedings of the International Conference on Image & Graphics, ICIG 2004", Hong Kong, December 2004, pp. 222–225.

[12] L. Zhang, D. Zhang, "Characterization of Palmprints by Wavelet Signatures via Directional Context Modeling", *IEEE Trans. Sys. Man Cybern. Part B (2004)*, 1335–1347.

[13] D. Zhang, W. Shu, "Two Novel Characteristics in Palmprint Verification: Datum Point Invariance and Line Feature Matching", *Patt. Recog.*, **32 (4)**, 1999, 691–702.

[14] A. Kumar, D.C.M. Wong, H. Shen, A.K. Jain, "Personal Verification using Palmprint and Hand Geometry Biometric", AVBPA, Guildford, UK, June 2003, pp. 668–675.

[15] X. Lu, D. Zhang, K. Wang, "Fisherpalms based Palmprint Recognition", **Patt. Recog. Lett.**, **24**, 2003, 2829–2838.

[16] G. Lu, D. Zhang, K. Wang, "Palmprint Recognition using Eigenpalm-like Features", *Patt. Recog. Lett.*, **24**, 2003, 1473–1477.

[17] W. Zuo, D. Zhang, K. Wang, An Assembled Matrix Distance Metric for 2DPCA-based Image Recognition Pattern Recognition Letters, **27**, 2006, 210–216.

[18] A. Kumar, D. Zhang, "Palmprint Authentication using Multiple Classifiers", *SPIE Symposium on Defense & Security—Biometric Technology for Human*

Identification, **5404**, Orlando, Florida, USA, April 12–16, 2004, pp. 20–29.

[19] A. Kong, D. Zhang, M. Kamel, “Palmprint Identification using Feature-level Fusion Pattern Recognition” **39**, 2006, 478 – 487.

[20] L. Nanni and A. Lumini, “Ensemble of Multiple Palmprint Representation”, *Expert Systems With Applications*, **36**, No.3, pp.4485-4490, April 2009.

[21] Q.Li, Z.Qiu, D.Sun, J.Wu: “Personal Identification Using Knuckleprint”, Sinobiometrics, 2004:680-689.

[22] S.Ribaric, I.Fratric, “A Biometric Identification System Based on Eigenpalm and Eigenfinger Features”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **27 (11)**, November-2005, 1698-1709.

[23] L. Nanni, A. Lumini, “On Selecting Gabor Features for Biometric Authentication”, *International Journal of Computer Applications in Technology*, **35 (1),** 2009, 23–28.

[24] Lin Zhang, Lei Zhang, David Zhang, and Hailong Zhu, “Online Finger-Knuckle-Print Verification for Personal Authentication”, *Pattern Recognition*, **43**, No. 7, pp. 2560-2571, July 2010.

[25] Rui Zhao, Kunlun Li, Ming Liu, Xue Sun, “A Novel Approach of Personal Identification Based on Single Knuckleprint Image,” *Apcip*, **2**, pp.218-221, 2009 Asia-Pacific Conference on Information Processing, 2009.

[26] D. Maio, D. Maltoni, A.K. Jain, S. Prabhakar, “Handbook of Fingerprint Recognition”, Springer, New York, 2003.

[27] A.K. Jain, S. Prabhakar, L. Hong, Pankanti S, “Filterbank-based Fingerprint Matching”, *IEEE Transactions on Image Processing*, **5 (9)**, 2000, 846 – 859.

[28] A. Ross, A. Jain, J. Reismanb, “A Hybrid Fingerprint Matcher”, *Pattern Recognition*, **36**, 2003, 1661 – 1673.

[29] A. Teoh, D. Ngo, O.T. Song, “An Efficient Fingerprint Verification System Using Integrated Wavelet and Fourier-Mellin Invariant Transform”, I*mage and Vision Computing Journal*, **22 (6)**, 2004, 503-513.

[30] G. de Sá, R. Lotufo, “Improved FingerCode Matching Function”, *XIX Brazilian Symposium on Computer Graphics and Image Processing (SIBGRAPI’06)*.

[31] J.A.M. Zegarra, N.J. Leite, R. da Silva Torres, “Wavelet-based Fingerprint Image Retrieval”, *To Appear in: Journal of Computational and Applied Mathematics 2008*.

[32] Jianjiang Feng, “Combining Minutiae Descriptors for Fingerprint Matching”, *Pattern Recognition*, **41**, Issue 1, January 2008, Pages 342-352.

[33] L. Nanni and A. Lumini, “A Hybrid Wavelet-based Fingerprint Matcher”, *Pattern Recognition*, **40**, (11) (November 2007) 3146-3151.

[34] F. Benhammadi, M.N. Amirouche, H. Hentous, K. Bey Beghdad, M. Aissani, “Fingerprint Matching from Minutiae Texture Maps”, *Pattern Recognition*, **40**, 2007, 189–197.

[35] L. Nanni, A. Lumini, “Local Binary Patterns for a Hybrid Fingerprint Matcher”, *Pattern Recognition* (2008), doi:10.1016/j.patcog.2008.05.013.

[36] L. Nanni and A. Lumini, “Descriptors for Image-based Fingerprint Matchers”, *Expert Systems With Applications*, **36**, No.10, pp.12414-12422, December 2009.

[37] N. Dalal, B. Triggs, “Histograms of Oriented Gradients for Human Detection”, *in: Proceedings of the 9th European Conference on Computer Vision*, San Diego, CA, 2005.

[38] R. Poppe, “Evaluating Example-based Pose Estimation: Experiments on the HumanEva Sets”, *CVPR 2nd Workshop on Evaluation of Articulated Human Motion and Pose Estimation*, 2007.

[39] Ojansivu V. and Heikkila J. (2008), “Blur Insensitive Texture Classification using Local Phase Quantization”, In ICISP 2008.

[40] Ahonen T, Matas J, He C & Pietikäinen M (2009), “Rotation Invariant Image Description with Local Binary Pattern Histogram Fourier Features”, Image Analysis, SCIA 2009 Proceedings, Lecture Notes in Computer Science 5575, 61-70.

[41] T. Connie, A.T.B. Jin, M.G.K. Ong, D.N.C. Ling, An Automated Palmprint Recognition System Image and Vision Computing, **23**, 2005, 501–515.

[42] A. Lumini and L. Nanni, “Two-class Fingerprint Matcher”, *Pattern Recognition*, **39**, No.4, pp.714-716, April 2006.

[43] Xin Pan, Qiu-Qi Ruan, “Letters: Palmprint Recognition using Gabor-based Local Invariant Features”, *Neurocomputing*, **72**, N.7-9, p.2040-2045, March, 2009.

[44] Baochang Zhang, Zongli Wang, Bineng Zhong, “Kernel Learning of Histogram of Local Gabor Phase Patterns for Face Recognition”, *EURASIP Journal on Advances in Signal Processing*, Volume 2008, Article ID 469109, 8 pages doi:10.1155/2008/469109 (2008).

[45] S. Fischer, F. Sroubek, L. Perrinet, R. Redondo, and G. Cristóbal. “Self-invertible Log-Gabor Wavelets”, *Int. Journal of Computer Vision*, **75 (2)**, p. 231-246, 2007.

[46] W. K. Kong, D. Zhang, “Competitive Coding Scheme for Palmprint Verification”, *in: Proceedings of the ICPR’04*, 2004, pp. 520–523.

[47] Z.H. Guo, D. Zhang, L. Zhang, W.M. Zuo, “Palmprint Verification using Binary Orientation Co-occurrence Vector”, *Pattern Recognition Letters*, 1219–1227, **30** (13), 2009.