# A Feature Extraction Method Based on the Pattern Spectrum for Hand Shape Biometry

Juan Manuel Ramirez-Cortes, Pilar Gomez-Gil, Gabriel Sanchez-Perez, and David Baez-Lopez

***Abstract***— **In this paper a novel feature extraction methodology based on the morphological pattern spectrum or *pecstrum*, for a hand-shape biometric system is proposed. The image of the right hand of a subject is captured in an unconstrained pose, with a commercial flatbed scanner. The invariance to rotation and position properties of the pecstrum allow the system to avoid a fixed hand position using pegs, as is the case in other reported systems. Identification experiments were carried out using the obtained feature vectors as the input to some recognition systems based on distance classifiers, neural networks, and support vector machines, for comparison purposes. The verification case was analyzed through an Euclidean distance classifier, obtaining the acceptance rate (FAR) and false rejection rate (FRR) of the system for some K-fold cross validation experiments. In average, an Equal Error Rate of 2.31 % was obtained. The results indicate that the pattern spectrum represents a good alternative of feature extraction for biometric applications.**

***Index Terms***—**biometry, pattern spectrum, hand-shape, recognition.**

## I. Introduction

Biometric systems for automated personal identification and verification have received extensive attention in the last years. These systems aim to provide automatic recognition of an individual based on some sort of unique physiological characteristics inherent of the person. Biometric systems are based on various modalities such as fingerprints, iris, voice, face, ear shape, hand shape, palm prints, or dynamical features like gait, on-line signature verification, and others [1]. Strength and weakness of each method related to some specific application and its requirements have been widely reported in the literature. Among these modalities, hand shape recognition has received significant attention due in part to its convenience on setup complexity, and its psychological acceptance as a non invasive method which do not cause any anxiety for the user as it could be possible with other techniques [2]. Hand-based biometric systems, however, are usually employed in small to medium scale person verification applications due to the fact that geometric features of the hand are not as distinctive as fingerprint or iris features [3]. In the last years some commercial systems have been developed, and new algorithms are being proposed. Many hand-based biometric techniques use geometric features such as finger and palm heights, finger widths, aspect ratio of the palm to fingers [4]-[5]-[6], palm print information, palm contour or a combination of palm print features and geometric measurements [7]-[2]. Several mathematical approaches for feature extraction have been proposed, such as Hausdorff distance [8], B-spline curves [9], geometric implicit polynomials [10], or high order Zernike moments [3]. Several references with excellent algorithm comparison analysis can be found in the literature [3]-[11]-[12]. In this paper, we propose the use of the morphological operator *pecstrum* or pattern spectrum, as a novel feature extractor for a shape-based hand recognition system. The properties of invariance to rotation and position of the pecstrum, provide flexibility to the system by allowing the user to pose naturally the hand without additional constraints. This is an advantage over some reported systems, where a fixed hand position using pegs is required.

J.M. Ramirez-Cortes is with the Electronics Department, National Institute for Astrophysics, Optics, and Electronics, Tonantzintla, Puebla, 72000, Mexico (phone/fax: 52-222-247-0517; e-mail: jmramire@inaoep.mx).

P. Gomez-Gil is with the Computer Department, National Institute for Astrophysics, Optics, and Electronics, Tonantzintla, Puebla, 72000, Mexico (e-mail: pgomez@inaoep.mx).

G. Sanchez-Perez is a postdoctoral student at the Electronics Department, National Institute for Astrophysics, Optics, and Electronics, Tonantzintla, Puebla, 72000, Mexico (phone/fax: 52-222-247-0517; e-mail: gabsan@inaoep.mx).

D. Baez-Lopez is with the Electrical and Computing Engineering Department, Universidad de las Americas, Puebla, 72000, Mexico ( e-mail: dbaeziec@gmail.com).

## II. MORPHOLOGICAL PATTERN SPECTRUM

Morphological image processing is a nonlinear theory and technique to quantitatively describe operations effective for the shape of objects in an image [13]-[14]. The morphological operators are described by combinations of a basic set of numerical manipulations between an image A and a small object B, called a *structuring element,* which can be seen as a probe that scans the image and modifies it according to some specified rule. The shape and size of B, typically much smaller than the image A, together with the specific rule, define the characteristics of the performed process. An interesting morphological operator is the *pattern spectrum or pecstrum*. This operator decomposes the target image in morphological components according to the shape and size of the structuring element, providing a quantitative analysis of the morphological content of the image [15]-[16].

Pecstrum was originally developed and reported by Maragos [16], and Venetsanopoulus [13]. Although it presents excellent properties as a shape extractor, with invariance to translation and rotation, pecstrum has not been extensively used, probably because it results computationally intensive in some applications, however, the available current hardware solutions easily overcome this disadvantage. We found that pecstrum has been used in the last years with several purposes: Analysis of partial discharges in high voltage systems [17], automatic recognition of automotive plates [18], texture analysis in several applications, such as images of debris particles in polymers and composite materials [19]-[20], and cytology of bone marrow images for the counting of white blood cells based on morphological granulometries [21]. In this paper, we propose the pattern spectrum as feature extractor for obtaining quantitative information regarding the hand shape for biometric purposes. Binary-image mathematical morphology is based on two fundamental operators extensively presented in the literature as d*ilation, and erosion* [13], defined as:

$$A \oplus B = \bigcup_{b \in B} T_b(A) \quad (1)$$

$$A \ominus B = \bigcap_{b \in B} T_{-b}(A) \quad . \quad (2)$$

The backbone of the pattern spectrum is the *opening* morphological filter, defined as an erosion followed by a dilation using the same structuring element. The opening operator is expressed as:

$$A \circ B = (A \ominus B) \oplus B \quad . \quad (3)$$

In the opening operator the dilation tries to undo the erosion operation, however, some details closely related to the shape and size of the structuring element will vanish. Furthermore, an object disappearing as consequence of the erosion can not be recovered. In a pattern spectrum the progressive vanishing of the image is numerically captured by measuring the differences in area in each step. Formally, the pattern spectrum of a compact binary image $A \subseteq R^2$, relative to a convex binary pattern $B \subseteq R^2$, is defined as the differential size distribution function:

$$P_x(n,B) = \frac{dM(A \circ nB)}{dn}, \qquad n \geq 0 \quad (4)$$

where $M$ represents the area measured in the intermediate operations, and $nB$ is the n-times dilated structuring element. The discrete form of the pattern spectrum is given by:

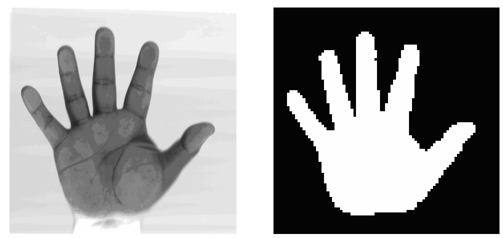
$$P(n,B) = \frac{M[A \circ nB] - M[A \circ (n+1)B]}{M[A]} \quad . \quad (5)$$

The *pecstrum* has the property of invariance to translation and rotation when B is an isotropic structuring element. Scale is determined by the size of the structuring element.

## III. FEATURE EXTRACTION

The images were acquired from the right hand of the subjects using a flatbed scanner in an unconstrained pose at 50 dpi, and reduced to a size of 256X256 pixels. The subjects were asked to stretch naturally their hand, and place it inside a square drawn on the scanner without additional restrictions.
A setup with lateral underlight illumination was used in order to automatically get rid of the area corresponding to the wrist, as it is shown in figure 1. The palm shape is then segmented by simple binarization and contrast inversion, with a gray level thresholding method using an experimentally determined threshold of 150, without additional processing. Figure 2 shows the pecstrum-based feature vector obtained from the hand-shape image in figure 1, with a structuring element given by a disk with an incremental ratio of 1 pixel per iteration. Figure 3 shows the feature vectors obtained from three different subjects. The first value corresponds to the total area of the hand-shape, and the rest are the values of the pattern spectrum obtained according to equation 3. The maximum vector length obtained was n=25, which corresponds to the last iteration in which the image vanishes.

In a typically obtained hand-shape pattern spectrum, the first value corresponded to the total area, the intermediate values reflected the morphological constitution of the fingers, and the last values came from the central palm shape. The execution time of erosion and dilation increases exponentially with the size of the structuring element. Furthermore, it was found that no additional information about the hand-shape was obtained in the last stages, due to the tendency of the central part of the hand to approximate a round form. Computation of the pecstrum was then optimized by increasing the step size of the structuring element in the last stages five times, when half the area of the shape-hand is surpassed.



**(a)** **(b)**

**Fig. 1** Feature extraction. (a) Gray scale captured image. (b) Binary segmented image.

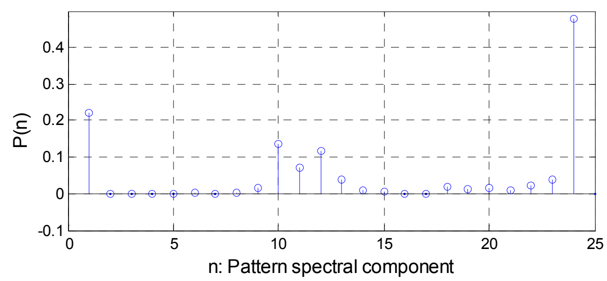



**Fig. 2** Pattern spectrum of the hand-shape in figure 1.

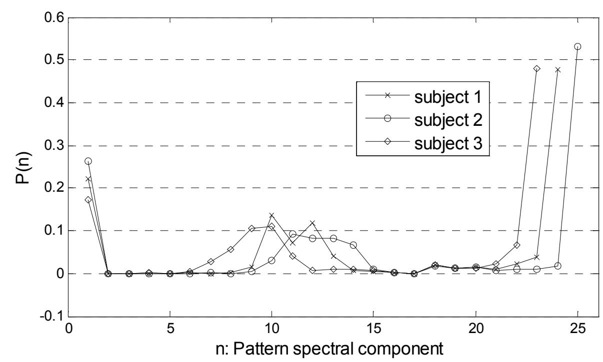



**Fig. 3** Comparison of the feature vectors obtained from three different subjects.

A group of 200 images of the right hand, 10 samples from each subject, for 20 subjects, was collected. A basic statistic analysis was performed in order to get initial information about the feature extraction methodology. The maximum distance between samples was 0.7989. The average distance between mean classes was 0.469664. The samples within each group of the same subject were located in clusters with an average mean distance and standard deviation of 0.04456 and 0.01232, respectively. The generated database included hand-shapes images with natural finger variations in the position between samples. Figure 3 shows two images obtained from the same subject, with an Euclidean distance of 0.05624 between their feature vectors. According to the obtained results, the pattern spectrum is able to tolerate finger displacements, and to extract a good representation of the morphological constitution of the hand shape.

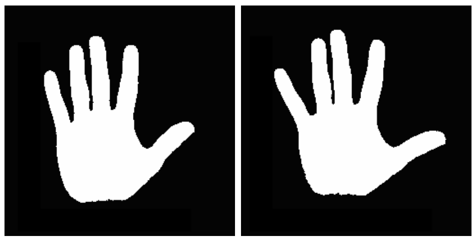


**Fig. 3** Two samples from the same subject with variation in the position of the fingers. The Euclidean distance between feature vectors is 0.05624.

## IV. CLASSIFICATION RESULTS

The novel feature extraction method based on the pattern spectrum was tested in a system for biometric purposes. In biometry the system performance is evaluated in two cases: Verification and identification. In the 'verification' case the system is expected to check the user claimed identity providing a binary answer in the form of 'accepted' or 'rejected'. In the 'identification' case the system is expected to identify who the user is, from a collection of classes stored in a database.

### *A. Experiments on 'verification'*

The described feature extraction methodology was tested for the 'verification' case with the 200 samples database using an Euclidean distance-based classification algorithm. A two-fold cross validation was carried out by dividing the database in two groups, with 5 samples per subject en each group. The first group was used as enrollment template, while the second group was used for the authentication process. The experiment was repeated 10 times, selecting randomly in each case the enrollment template. The performance was evaluated through the False Acceptance Rate (FAR) and False Rejection Rate (FRR), defined as follows:

$$FRR = \frac{\text{Number of false rejections}}{\text{Number of accesses}} \quad (6)$$

$$FAR = \frac{\text{Number of false acceptances}}{\text{Number of accesses}} \quad (7)$$

FRR and FAR present a tradeoff controlled by a decision threshold (DTH). This threshold represents the Euclidean distance which gives the separation point between matching and non-matching accesses. The Equal Error Rate (EER) is defined as the point in which FRR and FAR exhibit the same value. Figure 4 shows the obtained average FAR and FRR curves. The system performance is usually expressed through a Receiver Operation Characteristic plot (ROC), which represents the operating points of the system. The ROC curve is obtained from the FRR and FAR curves in figure 4, moving DTH across the range of the decision threshold. Figure 5 shows the average ROC curve obtained in this experiment. An Equal Error Rate (EER) of 0.0231 was obtained at a decision threshold of DTH =0.0675. Some average FRR and FAR in percentage values are shown in table I.

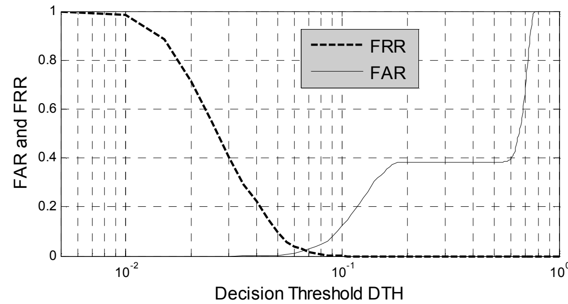



**Fig. 4** Average False Rejection Rate and False Acceptance Rate curves

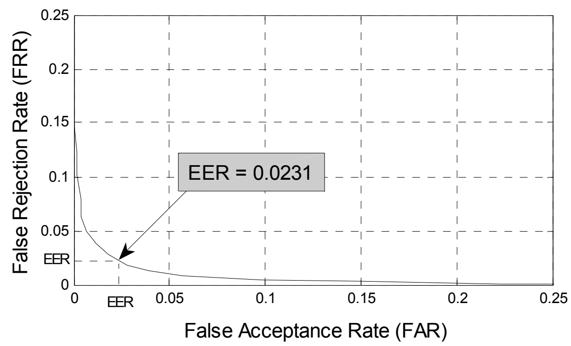



**Fig. 5** Average Receiver Operation Characteristic (ROC)

**Table I.** Average FRR and FAR in percentage values.

| Euclidean Distance Threshold DTH | FRR | FAR |
|---|---|---|
| 0.035 | 29.20 % | 0 |
| 0.045 | 15.00 % | 0.27 % |
| 0.060 | 3.90 % | 1.29 % |
| 0.0675 | 2.31 % | 2.31 % |
| 0.075 | 1.20 % | 3.86 % |
| 0.095 | 0.20 % | 10.2 % |
| 0.105 | 0 | 14.5 % |

### *B. Experiments on 'identification'*

For the identification experiments the following supervised classifiers were tested:

*Minimum Euclidean distance classifier*. The object under test is assigned to the nearest prototype (minimum Euclidean distance) among the N classes, where each prototype is obtained as the mean vector of the M samples in each class. In this work N=20, M=10.

*K-nearest neighbor classifier*. The class of the object is assigned to the most represented category among the k nearest samples of that object. In this work, the Euclidean distance is used as the similarity measure.

*Neural networks*. A feed forward single-layer perceptron trained with the Levenberg-Marquardt back propagation algorithm included in the NN toolbox of MATLAB, was used in this work. The network has 25 input nodes and 20 output nodes. All neurons used a sigmoid as an activation function. Figure 6 shows the error plot obtained after 36 epochs in one of the training sessions.

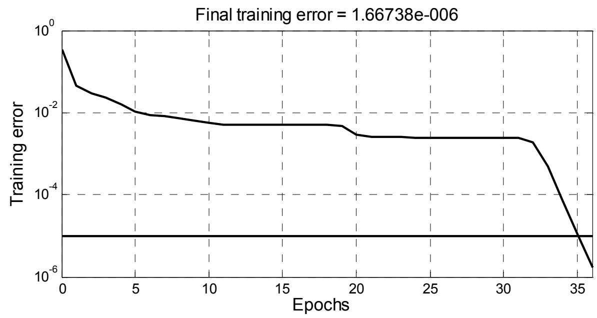



**Fig. 6** An example of training performance

*Support vector machines (SVM).* Briefly, SVM is described as a statistical learning method based on a structural risk minimization procedure [21]. Classification of the test sample x is performed by:

$$y = \operatorname{sgn}\left(\sum_{i=1}^{N} \alpha_i y_i K(s_i, x)\right), \qquad (8)$$

where N is the number of training samples, $y_i$ is the class label, $\alpha_i$ is the Lagrangian multiplier, the elements $x_i$ for which $\alpha_i > 0$ are the support vectors, and $K(s_i,x)$ is the function kernel. In this work a Gaussian radial basis was used.

In the four recognition methods used, a two-fold cross validation scheme was followed, using half of the samples for training and the other half of the samples for generalization. The experiments were repeated ten times, selecting both groups randomly in each case. Table II shows the average identification rate obtained with the four recognition systems previously described. These results are very competitive when they are compared with systems reported in the literature [3]-[11]-[12], although experiments with larger databases are needed.

**TABLE II.** Average identification rate obtained with four methods

| Recognition method | Average identification rate |
|---|---|
| Minimum Euclidean distance classifier | 97.2 % |
| k-nearest neighbor (k=3) | 98.0 % |
| Neural network | Training: 100 %<br>Generalization: 98.5 % |
| Support vector machine | 99.0 % |

## V. Conclusion

A novel hand-shape feature extraction for biometric applications, based on the morphological pattern spectrum has been presented. A comparison with results obtained from different feature extraction methods reported in the literature show a very competitive performance. The results on identification and verification experiments indicate that the pattern spectrum represents a good choice of feature extraction methodology for low and medium scale applications. Furthermore, the method could be enhanced by incorporating additional information, such as palm print features in a data integration manner.

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