Palm geometry biometrics: A score-based fusion approach

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Abstract In this paper we present an identification and authentication system based on hand geometry. First, we examine the performance of three different methods that are based on hand silhouette and on binarized hand images and then we investigate approaches for combining the feature vectors, identification-verification scores, and individual acceptance-rejections decisions taken by using each one of the proposed methods individually. The proposed system has been tested on the POLYBIO hand database which consists of 180 hand images from 45 individuals. The experiments show that fusion of feature vectors results in a slightly better performance in both identification and authentication tests while combination of scores and decisions leads to a significant improvement in authentication performance and minor improvement in identification.

1 Introduction

Biometrics technology aims to identify biological and behavioral features that are considered unique to a person and use them for authentication control in accessing secured places or devices. Biometric authentication systems are based on various modalities such as hand, iris, fingerprints, voice and face [7]. Fingerprints are by far the most widely used biometric for identification while iris is used for authentication control for large populations (i.e. at airports instead of using passports). Facial images are used in passport control for identification but the actual test involves the comparison of the photograph on the passport with the one stored in the database;

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that is, it stills based on something that one carries (passport) than something related with her/his live instance (face in this particular example). Speech recognition based authentication systems prove to be cost effective for simple access control implementations but cannot be used in high security zones. Finally, behavioral biometrics is an emerging technology not mature enough yet to be used in real life authentication or identification tasks.

Hand-geometry based authentication systems are gaining importance because they provide a good compromise between performance, cost of implementation and intrusiveness for security applications involving low to medium user population. Unfortunately as the user population increases the efficiency of hand-geometry based systems decreases [8]. However, combination with other forms of biometrics like fingerprint and palmprint is easy and can significantly increase the confidence levels in both identification and authentication procedures. The major advantage of hand geometry verification systems is the ease of image acquisition compared to the other biometric modalities. The acquisition system simply requires a properly placed camera that can get the image of the hand. Additional advantages of hand geometry systems include user-friendliness, non intrusiveness, and low template storage cost.

Hand geometry authentication systems based either on hand silhouette [8] [15] or on measurements extracted from palm and hand [14] [10]. The latter systems lead, in general, to better authentication performance but they are very sensitive to the localization of hand-extreme points based on which measurements are recorded [5]. Hand silhouette based systems, on the other hand, are much more robust, they have a compact mathematical representation and require less pro-processing effort.

In this paper we present three methods for hand geometry based identification and authentication. The two of them are based on hand silhouettes and involve Fourier descriptors and power spectrum estimation respectively, while the third uses the region and contour shape descriptors, proposed in MPEG-7 framework [6], extracted using the binarized hand image. In addition simple area measurements extracted from the binarized hand image are also examined for comparison purposes. In a further step we investigate feature, score and decision based fusion of the above-mentioned methods in order to increase the authentication and identification rates.

The paper is organized as follows: In Section 2 we present the hand image acquisition system. Section 3 is devoted to the description of the individual methods for hand geometry authentication and identification. The proposed fusion methodology is explained in Section 4. In Section 5 we present the evaluation protocol we have employed along with extended experimental results. Finally conclusions are drawn and further work hints are given in Section 6.

2 Image acquisition

The multibiometric data were collected through the use of an integrated platform that was created in the framework of project POLYBIO [9]. The scenario in the acquisition process was an office room where the acquisition hardware and software could be operated by a system supervisor, guiding the steps of the test subjects through the data collection procedure. Environmental conditions such as lighting or background noise were not controlled so as to simulate a realistic situation. The data acquisition system is depicted in Figure 1.

The process of collecting hand images is completed with the aid of the interactive panel shown in Figure 2. The user is prompted by the supervisor to place his/her left hand facing down-wards on the black board panel with the six positioning pins (pegs). The facing down-wards camera is activated and the palm images are taken, which if they are considered by the system supervisor of good quality, they are stored in the database. A total of four palm images are collected for each individual. The acquired palm images are of 240 pixels length x 320 pixels width, color ones (RGB model) and they are compressed using the JPEG compression scheme (quality 80%). More information on the palm image acquisition procedure can be fount at [1].

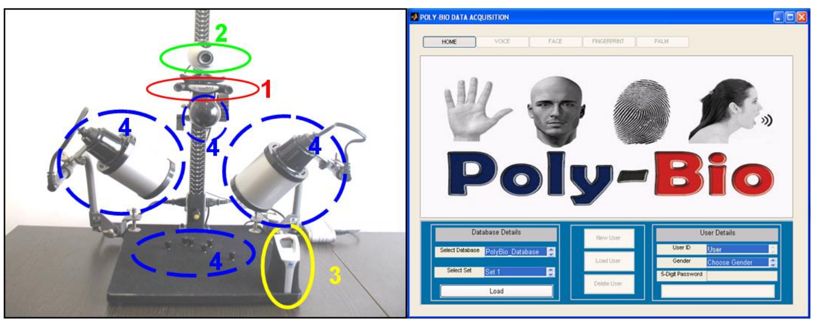

Fig. 1 The POLYBIO multibiometric data acquisition system

Fig. 2 Interactive panel for hand image acquisition

3 Biometric template creation

The biometric templates that are created from the hand images are based either on the palm contour or on the palm area. In both cases binarization of hand images is required. We used for this purpose a simple threshold approach. The threshold is obtained using the Otsu's method [11]. In a subsequent step morphological processing (the closing operator was applied) is adopted in order to fill in holes within the palm area.

3.1 The Fourier descriptor template

The first template was created using the Fourier descriptors of the palm contour. Let us consider the palm contour as a function of a complex variable $z(n) = x(n) + jy(n)$, $n = 0, 1, ..., M-1$, where M is the number of contour points and $(x(i), y(i))$ are the $2D$ coordinates of the i-th point. By taking the Fourier expansion of $z(n)$ we get:

$$a(k) = \sum_{m=0}^{M-1} z(m) \cdot e^{\frac{-2j\pi km}{M}}, \quad 0 \le k \le M-1 \tag{1}$$

The Fourier descriptors are the normalized amplitude coefficients of the Fourier series:

$$F_d(k) = \frac{a(k)}{\|\mathbf{a}\|}, \quad \|\mathbf{a}\| = [F_d(1)\ F_d(2) ...\ F_d(M)] \tag{2}$$

The Fourier descriptors actually indicate the frequencies of the curve changes along the contour. For denoising purposes palm contour is first approximated using 64 Fourier coefficients.

3.2 The power spectrum template

Assuming second order stationarity an approximation of palm contour's autocorrelation function is given by:

$$R(k) = \frac{1}{(M-k) \cdot \|\sigma\|} \sum_{m=0}^{M-1-k} (z(m) - \mu) \cdot (z(m+k) - \mu), \quad k < M-1 \tag{3}$$

where μ denotes the coordinates of contour's centroid and σ is the variance of contour's coordinates.

Taking the discrete Fourier transform of autocorrelation series lead us to an estimation of the contour's power spectrum:

$$PSD(k) = \sum_{m=0}^{M-1} R(m) \cdot e^{\frac{-2j\pi km}{M}}, \quad 0 \leq k \leq M-1 \tag{4}$$

The magnitude of PSD coefficients is used to describe the contour (only the coefficients with high energy value are used).

3.3 Area measurements

The following measurements of the binarized hand image were used to create another simple template:

1. *Ratio of Minor to Major axis length*: The minor to major axis length is the length (in pixels) of the minor /major axis of the ellipse that has the same normalized second central moments as the palm area.
2. *Solidity*: The proportion of the pixels in the convex hull that are also in the region (ratio of Area / ConvexArea).
3. *Extent*: It represents the pixels in the bounding box that are also in the palm region. It is computed as the Area divided by the area of the bounding box.
4. *Ratio of area to image dimensions*: Area refers to the actual number of pixels in palm region.
5. *Eccentricity*: Corresponds to the ratio of the distance between the foci of the ellipse and its major axis length. The value is between 0 and 1 (0 and 1 are degenerate cases; an ellipse whose eccentricity is 0 is actually a circle, while an ellipse whose eccentricity is 1 is a line segment).
6. *Ratio of area to image dimensions*: It is computed as $\frac{Perimeter \times \pi}{Area}$
7. *Equivalent diameter / Major axis length*: Equivalent diameter is the diameter of a circle with the same area as the palm region. It is computed as $\sqrt{\frac{4 \cdot Area}{\pi}}$.

3.4 The MPEG-7 visual descriptor template

MPEG-7 visual descriptors include the color, texture and shape descriptor. A total of 22 different kind of features are included, nine for color, eight for texture and five for shape. The various feature types are shown in Table 1. In the third column of this Table is indicated whether or not the corresponding feature type is used in holistic image and/or object description. The number of features shown in the fourth column in most cases is not fixed and depends on user choice; we indicate there the settings in our implementation.

Four different templates were created from the hand image, corresponding to the Color Layout (CL) descriptor, the Contour Shape (CS) descriptor, the Region Shape (RS) descriptor, and the Edge Histogram (EH) descriptor. The features of these descriptors were computed using the MPEG-7 experimentation model [12].

Table 1 MPEG-7 visual descriptors used to create hand image templates

Descriptor	*Type*	*# of features*	*Usage level*	*Comments*
Color	DC coefficient of DCT (Y channel)	1	Both	Part of the Color Layout descriptor
	DC coefficient of DCT (Cb channel)	1	Both	Part of the Color Layout descriptor
	DC coefficient of DCT (Cr channel)	1	Both	Part of the Color Layout descriptor
	AC coefficients of DCT (Y channel)	5	Both	Part of the Color Layout descriptor
	AC coefficients of DCT (Cb channel)	2	Both	Part of the Color Layout descriptor
	AC coefficients of DCT (Cr channel)	2	Both	Part of the Color Layout descriptor
	Dominant colors	Varies	Both	Includes color value, percentage and variance
	Scalable color	16	Both	
	Structure	32	Both	They used in both holistic image and image segment description
Texture	Intensity average	1	Both	Part of the Homogeneous Texture descriptor
	Intensity standard deviation	1	Both	Part of the Homogeneous Texture descriptor
	Energy distribution	30	Both	Part of the Homogeneous Texture descriptor
	Deviation of energy's distribution	30	Both	Part of the Homogeneous Texture descriptor
	Regularity	1	Both	Part of the Texture Browsing descriptor
	Direction	1 or 2	Both	Part of the Texture Browsing descriptor
	Scale	1 or 2	Both	Part of the Texture Browsing descriptor
	Edge histogram	80	Both	Includes the spatial distribution of five types of edges
Shape	Region shape	35	Segment	A set of angular radial transform coefficients
	Global curvature	2	Both	Part of the Contour Shape descriptor
	Prototype curvature	2	Both	Part of the Contour Shape descriptor
	Highest peak	1	Both	Part of the Contour Shape descriptor
	Curvature peaks	Varies	Both	Describes curvature peaks in term of amplitude and distance from highest peak

4 Fusion methodologies

Two basic fusion methodologies were examined in order to identify whether or not fusion of different templates (even from the same modality) can enhance the performance of a hand-based biometric system. We first examined feature based fusion; that is the feature vectors of templates created using the previous methods where concatenated in various combinations (see also Table b 2).

Score based fusion was performed in two steps: We first normalized the scores achieved using the various templates by dividing with the highest threshold for each method so as the thresholds to lie in the interval [0 1]. Normalization is very important because non-normalized scores lead to performance lower to that obtained by feature based fusion. The second step includes weighting of scores so as the template with the better performance to contribute more in the total score. As in feature based fusion various combinations were examined. The results are summarized in Table 2

5 Evaluation protocol and experimental results

Evaluation was based on the POLYBIO multimodal biometric database [1] which contains samples from voice, face, palm and fingerprint for 45 individuals. Four data capture sessions were stored for each biometric. In our experiments we used the palm images of this database. Three images per individual were used for training and one for testing.

Let us denote with $\mathbf{f}_j^k$ the j-th ($j = 1,...,3$) palm feature vector of the k-th subject ($k = 1,2,...,N$). This feature vector is obtained with one of the methods described in Section 3. We also denote with $\mathbf{y}^k$ the feature vector used for testing. Due to the limited number of training instances per subject (i.e., three) we consider as the biometric template of the k-th subject the matrix:

$$\mathbf{F}^k = [\mathbf{f}_1^k \;\; \mathbf{f}_2^k \;\; \mathbf{f}_3^k] \tag{5}$$

It is obvious that many different templates can be constructed depending on the number of training vectors. Gaussian models and Neural Network representations are among the most popular approaches for template construction and user modeling. In our case we have implicitly consider that all training instances serve as Support Vectors [3].

For each subject we also define a threshold:

$$T^k = max_{i \neq j}(||\mathbf{f}_i^k - \mathbf{f}_j^k||) \tag{6}$$

False Rejection (FR) and False Acceptance (FA) are then defined as:

$$FR \Leftarrow min_j(||\mathbf{y}^k - \mathbf{f}_j^k||) > T^k \tag{7}$$

$$FA \Leftarrow min_{j,\ l \neq k}(||\mathbf{y}^l - \mathbf{f}_j^k||) < T^k \tag{8}$$

We evaluated the palm biometric by using a four folder cross validation approach. Three instances per subject were randomly selected and used as training patterns while the fourth was used for testing. We repeated this process for 20 cycles and for each one of the individual and feature based fusion methods. The average results are shown in the Table 2. In this table it is also shown the results of the score based fusion approach for the combination of several types of features.

We used two widely known evaluation metrics: EER (equal error rate, i.e. FA = FR) and Identification Error (IE). An identification error occurs in cases where the best matching stored template does not belong to the individual that attempts to enter the system.

Among all individual template methods the Color Layout (CL) performs better in both IE (5.71%) and EER (6.29%). Disappointing results were obtained from the Contour Shape (CS) descriptor althiugh this descriptor was defined for retrieval of image objects. In contrary Edge Histogram (EH) descriptor provides also satisfactory rates although was defined for texture (and not object) description.

In feature based fusion the best results were obtained by concatenating the Color Layout, Contour Shape and Edge Histogram descriptors. This is a quite logical result because these descriptor provide complementary information (color, contour and texture). If we take into account the dimensionality of fused template then excellent results are also obtained by combining the Color Layout and Contour Shape descriptors.

In score-based fusion several combinations lead to satisfactory results. The best results in terms of IE (0%) were obtained using a combination of Color Layout, Contour Shape and Contour Shape descriptors. At the same time a combination of Color Layout, Contour Shape and Edge Histogram descriptors leads to the best performance in terms of EER (2.12%).

Table 2 Evaluation results for the individual and fusion based methods in terms of identification error (IE) and equal error rate (EER)

Method	*Features*	*# of features*	*IE (%)*	*EER (%)*
FD	Fourier descriptors	8	20.00	14.15
FD	Fourier descriptors	16	11.43	14.61
FD	Fourier descriptors	32	12.14	16.62
PS	Power spectrum coefficients of contour	8	20.71	14.18
PS	Power spectrum coefficients of contour	16	13.57	13.84
PS	Power spectrum coefficients of contour	24	15.00	16.10
AF	Area related features	7	10.00	7.30
CL	MPEG-7: Color layout descriptor	12	5.71	6.29
CS	MPEG-7: Contour shape descriptor	5	43.57	15.48
RS	MPEG-7: Region shape descriptor	35	12.86	11.75
EH	MPEG-7: Edge histogram descriptor	80	10.71	7.16
FF1	Concatenated FD and PS	32	10.00	14.89
FF2	Concatenated FD and AF	23	6.43	9.93
FF3	Concatenated PS and AF	23	4.29	8.06
FF4	Concatenated CL and CS	17	1.43	3.87
FF5	Concatenated CL and RS	47	3.57	4.91
FF6	Concatenated CL and EH	92	3.57	3.33
FF7	Concatenated CS and RS	40	8.57	8.36
FF8	Concatenated CS and EH	85	5.00	5.76
FF9	Concatenated RS and EH	115	4.29	5.79
FF10	Concatenated FD, PS and AF	39	5.71	10.46
FF11	Concatenated CL, CS and RS	52	3.57	4.20
FF12	Concatenated CL, CS and EH	97	1.43	2.06
FF13	Concatenated CL, RS and EH	127	1.43	2.28
FF14	Concatenated CS, RS and EH	120	3.57	4.82
SF1	Score fusion of FD and PS	32	9.29	14.73
SF2	Score fusion of FD and AF	23	4.29	7.47
SF3	Score fusion of PS and AF	23	4.29	6.81
SF4	Score fusion of CL and CS	17	0.71	4.16
SF5	Score fusion of CL and RS	47	0.00	4.55
SF6	Score fusion of CL and EH	92	1.43	2.85
SF7	Score fusion of CS and RS	40	9.29	7.78
SF8	Score fusion of CS and EH	85	5.00	5.32
SF9	Score fusion of RS and EH	115	4.29	5.09
SF10	Score fusion of FD, PS and AF	39	2.86	7.30
SF11	Score fusion of CL, CS and RS	52	0.00	2.73
SF12	Score fusion of CL, CS and EH	97	0.71	2.12
SF13	Score fusion of CL, RS and EH	127	0.71	2.66
SF14	Score fusion of CS, RS and EH	120	2.86	4.52

6 Conclusion

In this work, we have presented an experimental study on palm geometry verification. The performance of several feature types including Fourier descriptors, power spectrum coefficients of palm's contour, area related measurements, and MPEG-7 visual descriptors was investigated. In addition both feature based and score based fusion was examined. Evaluation was based on 180 palm images obtained by 45 different users. The results indicate that: (1) Score based fusion provides the best results both in terms of equal error rate (EER) and identification error (IE), (2) both score based and feature based fusion lead to much better results than single method approaches, (3) Non-contour features, like the MPEG-7 color layout and edge histogram descriptors enhance the performance of the system but their robustness needs to be re-evaluated on data (hand images) obtained during different time periods, and (4) the best result is obtained by combining three MPEG-7 descriptors (color layout, contour shape, region shape) using score based fusion.

Future work includes the evaluation of the proposed score based fusion method on a larger dataset. We plan to use the data of the Biosecure Network of Excellence [2]. This network has been promoting since 2004 the development of biometric reference systems and reference databases. In addition decision based fusion and alternative score based fusion methodologies will be examined.

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