Pattern Recognition Letters 68 (2015): 183 – 189

DOI: http://dx.doi.org/10.1016/j.patrec.2015.09.011

Pattern Recognition Letters
journal homepage: www.elsevier.com

Synthesis of Large Scale Hand-Shape Databases for Biometric Applications

Aythami Morales [a*], Miguel A. Ferrer [b], Raffaele Cappelli[c], Davide Maltoni[c], Julian Fierrez[a], Javier Ortega-Garcia[a]

[a]ATVS-Universidad Autonoma de Madrid, C\Francisco Tomas y Valiente, 28049 Madrid, Spain.
[b]IDeTIC-Universidad de Las Palmas de Gran Canaria, Campus de Tafira, E35017 Las Palmas, Spain.
[c]Biometric System Laboratory, DISI-University of Bologna, Cesena (FC), Italy.

ABSTRACT

This work proposes and analyzes a novel methodology for hand-shape image synthesis. The hand-shape is a popular biometric trait with a high convenience of use and non-intrusive acquisition. The proposed algorithm allows to generate realistic images with natural intra-person and inter-person variability. The method is based on the Active Shape Model algorithm which has been modified in order to add the biometric information typical of new synthetic identities. The generated images are evaluated using three public databases and two hand-shape recognition systems. The results show the suitability of the synthetic data for biometric recognition works. In addition, two novel applications have been proposed to provide new insights in hand-shape biometric recognition including: improvement of machine learning classification based on synthetic training sets and scalability analysis of hand-shape biometrics when the population of the database is increased by two orders of magnitude with respect to existing databases.

1. Introduction

Biometric recognition technologies play an increasingly important role in security applications. The reliable authentication of people is crucial in nowadays digital society and biometric recognition provides the tools for improving the security of systems and services. In last decades many technologies have been proposed based on different human physical or behavioral traits: fingerprint, face, iris, hand-shape, palmprint, signature, gait, voice, keystroke, among many others.

The research community has invested time and efforts to improve the performance of biometric recognition systems. Technology evaluations require large scale datasets and their acquisition is time consuming and problematic (Ortega-Garcia et al., 2010). The privacy and legal concerns related with biometric data make difficult the promotion of large acquisition campaigns and most of the research work in the literature comprise experiments with few hundreds of users. Initially, the synthesis of biometric data emerges as a solution to the lack of large scale biometric databases. Additionally, synthetic databases have several applications such as performance evaluation (Cappelli et al., 2006; Maltoni et al. 2009), security assessment (Gomez-Barrero et al., 2014), modelling (Plamondon et al., 2014) or improving enrollment (Galbally et al., 2009).

The synthesis of biometric samples involves challenging tasks related with the natural variability modelling. The generation process involves modelling the patterns related with the biometric traits as well as the intra-person and inter-person variability inherent to real data. Synthetic databases are important for both research and industry because of the lack of large-scale databases derived from the difficulties of data collection; and the privacy/legal concerns related with the use of biometric information from real people.

Researchers have proposed models to generate the most popular biometric traits as fingerprint (Cappelli, 2009; Zhao et al., 2012), face (Blanz and Vetter, 1999), iris (Venugopalan and Savvides, 2011; Galbally et al., 2013; Cardoso et al., 2013), palmprint (Zhuoshi et al., 2008; Feng et al., 2011; Morales et al., 2014) or signature (Rabasse et al., 2008; Galbally et al., 2012a; Galbally et al., 2012b; Ferrer et al., 2014). However, the synthesis of databases for hand-shape biometric applications remains unexplored. The hand-shape biometric recognition systems become popular in 90's because of: i) its convenience and non-intrusive acquisition; ii) low-cost hardware requirements and; iii) its acceptability to the public. While hand-shape biometrics is a well-investigated subject in the literature, to the best of our knowledge, there are no proposals for automatic generation of hand-shape images. In this paper we introduce a novel method for the generation of synthetic hand-shape images for biometric applications.

The main contributions in this work can be summarized as

* Corresponding author: aythami.morales@uam.es

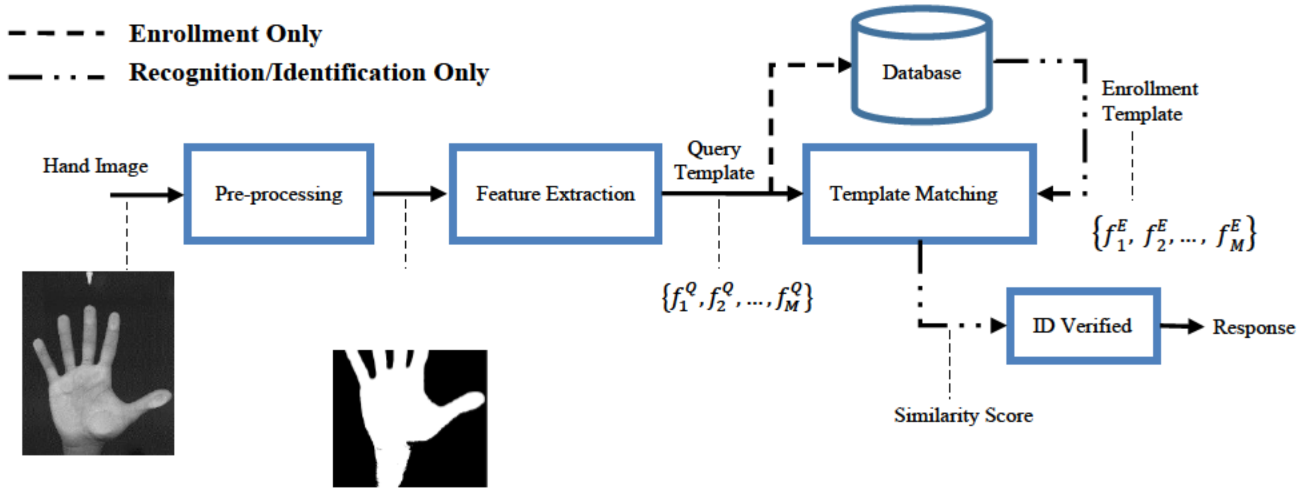


Fig. 1: Block diagram of a traditional hand-shape biometric recognition system

follow: i) a comprehensive method to synthetically generate hand-shape images which comprise the natural intra-person and inter-person variability; ii) an extensive analysis of the performance of two biometric recognition algorithms when using synthetic and real samples; iii) two novel applications of synthetic databases which reveal new insights on hand-shape recognition approaches; iv) a synthetic database including 100,000 identities and 500,000 samples is made freely available for the research community[2].

The rest of this paper is organized as follows: Section 2 describes related works; Section 3 introduces the hand-shape generation method and Section 4 presents the evaluation of the synthetic data; and Section 5 introduces two novel applications of the synthetic samples. Finally, Section 6 draws some conclusions.

2. Related Works

The generation of hand-shapes is not new and it has been proposed previously. In (Cootes et al., 1995) authors used the concavities of the hand to show the potential of the Active Shape Models (ASM) for border detection in images. The generation of hand-shape was proposed in (Gomez-Barrero et al., 2014) for vulnerability assessment of hand-shape recognition systems. This work proposed a hill-climbing algorithm, in combination with an ASM hand-shape synthesizer, to reconstruct the hand-shape from the templates stored in the databases of recognition systems. The main aim of the generation method proposed there was to reconstruct hand images from the templates, so it is a special case of synthesis (new identities are not generated). Finally, hand-shape synthesis (Feng et al., 2011; Morales et al., 2014) has been integrated as part of hand-print generation focused on ridge-line patterns. The aim of the hand-shape synthesizer in the previous work (Morales et al., 2014) was the generation of realistic hand-shape contours (in terms of appearance exclusively) to be integrated in the hand-print model. The hand-shape synthesizer was only briefly described and not studied as a biometric modality.

Hand-shape generation has been explored and proposed in previous work but for the best of our knowledge, its usefulness for database generation (composed by synthetic identities) and hand-shape applications remains unknown.

3. Hand-Shape Synthesis

Traditional hand-shape recognition approaches can be divided into three main modules: preprocessing, feature extraction and matching. The main aim of the preprocessing phase is to prepare the images for the subsequent feature extraction. The first steps of the preprocessing involve the conversion from color/grayscale hand images into black and white images, see Fig. 1. Most of the feature extraction and matching techniques in the hand-shape recognition literature (Duta, 2009; Ferrer and Morales, 2011; Kang and Wu, 2014; Sharma et al., 2015) are based on the silhouette of the hand or geometric features derived from it (e. g. widths, lengths, angles, aspect ratios, areas). All these approaches extract features from black and white hand images.

Instead of grayscale/color hand images, the generation method proposed in this work focus on the synthesis of binary hand-shapes which can be used in biometric applications. The generated images lack texture (more appropriate for palmprint/fingerprint approaches). The hand-shape generation process proposed in this work can be divided into two main tasks:

- **Generation of Master Hand-Shapes** (modeling the inter-person variability): the aim of this task is to generate a realistic master hand-shape which includes the biometric information of a specific synthetic identity. The biometric information comprises the patterns related with each individual as aspect of the hand, sizes and shapes, among others.
- **Generation of Multiple Samples from a Master Hand-Shape** (modeling the intra-person variability): the aim of this task is to model the natural variability between acquisitions of hand images from the same person. These variations include rotation, finger movement and minor changes in the shape due to elasticity of the skin.

The next subsection will detail the methodology proposed to automatically generate large scale synthetic databases.

3.1. Generation of a Master Hand-Shape

Our hand-shape synthesis is based on the Active Shape Model algorithm (Cootes et al., 1995). The parameters of the synthesizer are calibrated using the publicly available GPDSHand database (Ferrer et al., 2007). This database includes 10 images from 144 people acquired using a commercial document scanner. Segmentation can be

[2] http://atvs.ii.uam.es/databases.jsp

Fig. 2: Mean-Shape obtained from multiple hand contours from GPDSHand database

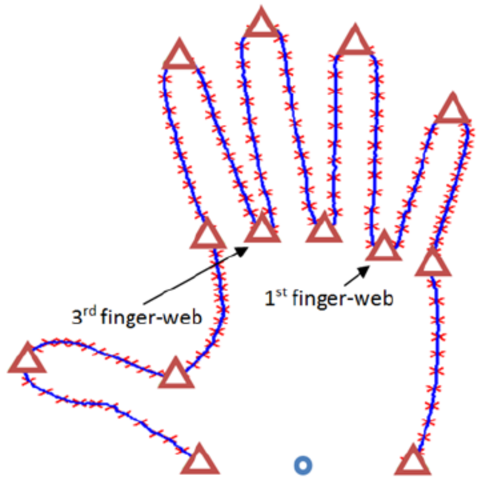


Fig. 3: An example with $n = 120$ equally spaced points (red crosses) of synthetic hand-shape (in continuous blue line), the corresponding fingertip and finger-web points (red triangles) and the center of the base of the hand (blue circle)

performed by applying Otsu thresholding. Once we obtain the binary images, the contour is represented as a $2n$ element vector composed by the $\{x, y\}$ Cartesian coordinates of $n = 1300$ equally-spaced points. The contours are aligned by placing the hand geometric center as the coordinate origin and rotating the hand contour by an angle defined by the first and third finger-web (see Fig. 2 and Fig. 3). This normalization allows to reduce the effects of translation, rotation and scale in the generation model.

The training set is therefore composed by 1440 aligned contours of dimension equal to 2600. The mean contour $\bar{\mathbf{c}}$ (see Fig. 2) is obtained as:

$$\bar{\mathbf{c}} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{c}_i \tag{1}$$

being $\mathbf{c}_i$ the i^{th} aligned contour (as a column vector) of the training set and N the number of training contours (N is equal to 1440 in our model). The principal axes of a $2n$ dimensional ellipsoid fitted to the data can be calculated by applying a Principal Component Analysis (PCA) to the data (Jolliffe, 2002). Each axis gives a mode of variation, a way in which the contour points tend to move together as the shape varies. For each shape in the training set we calculate its deviation from the mean, $\partial\mathbf{c}_i$, where:

$$\partial\mathbf{c}_i = \boldsymbol{c}_i - \bar{\mathbf{c}} \tag{2}$$

We can then calculate the $2n \times 2n$ covariance matrix $\mathbf{S}$ as:

$$\mathbf{S} = \frac{1}{N}\sum_{i=1}^{N}\partial\mathbf{c}_i\partial\mathbf{c}_i^{\mathrm{T}} \tag{3}$$

where $(\cdot)^{\mathrm{T}}$ denotes transpose. The principal axes of the ellipsoid, giving the modes of variation of the points of the shape, are described by $\mathbf{p}_k$ $(k = 1, \ldots, 2n)$, the unit eigenvectors of $\mathbf{S}$ such that:

$$\mathbf{S}\mathbf{p}_k = \lambda_k\mathbf{p}_k \tag{4}$$

where λ_k is the kth eigenvalue of $\mathbf{S}, \lambda_k \geq \lambda_{k+1}$ and

$$\mathbf{p}_k^{\mathrm{T}}\mathbf{p}_k = 1 \tag{5}$$

A master hand-shape $\mathbf{h}$ can be generated using the mean shape and a weighted sum of these deviations obtained from the first t modes as

$$\mathbf{h} = \bar{\mathbf{c}} + \mathbf{P}\mathbf{b} \tag{6}$$

Where $\mathbf{P} = [\mathbf{p}_1, \mathbf{p}_2, \ldots, \mathbf{p}_t]$ is the matrix of the first t eigenvectors and $\mathbf{b} = [b_1, b_2, \ldots, b_t]^{\mathrm{T}}$ is a vector of weights.

TABLE I. EFFECTS OF VARYING THE FIRST SIX MODES OF VARIATION IN THE ASM HAND-SHAPE GENERATION ALGORITHM

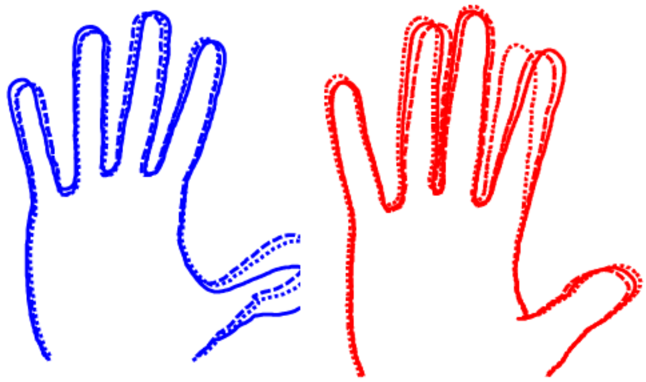
Mode	Effects on
p_1	Hand size/area
p_2	Hand rotation
p_3	Finger spread
p_4	Finger spread
p_5	Hand rotation + Finger spread
p_6	Hand rotation + Finger spread

Modifying $\mathbf{b}$ in the range $-3\sqrt{\lambda_k} \leq b_k \geq 3\sqrt{\lambda_k}$ we can obtain different hand-shapes. In our experiments, the first 12 eigenvectors or modes of variation cover 96% of the variance in the training set. The effects of varying the first 6 modes of variations can be easily recognized in the generated shapes and Table 1 summarizes such effects. The rest of modes show a combination of effects (e.g. size, shape, rotation, spread) more difficult to isolate.

The process to generate a master hand-shape is summarized as follows: i) the design database (GPDSHand database in our experiments) is processed to obtain the mean contour $\bar{\mathbf{c}}$, the eigenvectors $\mathbf{P}$ and eigenvalues λ_k; ii) a vector $\mathbf{b}$ is randomly generated according a normal distribution with zero mean and variance equal to $3\sqrt{\lambda_k}$; iii) the contour of the master hand-shape is generated according equation (6) and the binary image is obtained using a flood-fill morphological operation. The resulting images can be seen in Fig 5.a. Once a master hand-shape has been generated, the fingertips and finger-webs, which determine the location and size of fingers and palm, are automatically extracted according the methodology proposed in (Ferrer and Morales, 2011) (see Fig. 3). These key-points will be used in the subsequent generation steps to simulate finger movement and shape variations.

3.2. Generation of Multiple Samples from a Master Hand-Shape

The multiple samples are generated adding natural variability to each of the master hand-shapes. First of all, the position of the fingers in the GPDSHand database is analyzed to better understand the variability showed by different samples of real people. Once the hand position is normalized (see *Section 3.1*), we measured: a) the angles of the finger axis and b) its intra-person and inter-person standard deviation (see

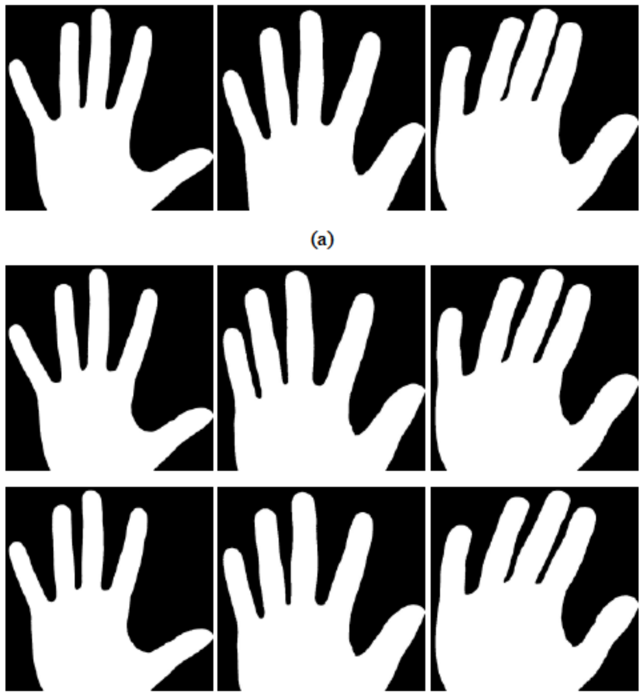


(a) (b)

Fig. 4: Real intra-person variability (a) and synthetically generated intra-person variability (b)

TABLE II. MEAN ANGLE (DEVIATION RESPECT AN IMAGINARY VERTICAL LINE CENTERED IN THE MIDDLE OF THE FINGER BASE), THEIR INTRA-PERSON AND INTER-PERSON STANDARD DEVIATION FOR EACH FINGER: THUMB (T), INDEX (I), MIDDLE (M), RING (R) AND LITTLE (L)

Mode	T	I	M	R	L
Mean angle	-12.3°	-9.0°	1.5°	9.9°	25.9°
Intra-p std	5.1	2.7	2.3	2.8	4.0
Inter-p std	8.7	4.8	4.8	5.5	6.9



(a)

(b)

Fig. 5. Examples of Master Hand-Shapes (a) and Multiple Impressions (b)

Table II). According to these measures we can observe that: i) the peripheral fingers (Thumb and Little) show higher variability than the rest of the fingers (Middle, Ring and Index); ii) the intra-person variability is near half the inter-person variability.

In our generation model we introduce the following sources of variability:

i) Finger-movement: the movement of the fingers is one of the most important factors on different samples of hand acquisition. Due to the elasticity of the skin, this movement has an impact in both position and shape of the hand, see Fig. 4.a. The finger movement is introduced as follows: i) the position of all fingers in the master hand-shape is established to the mean values showed in TableII; ii) two random rotation angles $\Delta\alpha_i$ (modeling the inter-person variability) and $\Delta\beta_i$ (modeling the intra-person variability) are assigned to each finger. $\Delta\alpha_i$ is fixed for all the samples of the same synthetic identity and ranges $\mp 9°$. $\Delta\beta$ ranges $\mp 5°$ and varies for each sample; ii) the position of the finger is changed applying an affine transform to the $\mathbf{f}_i = [x, y]$ coordinates of each finger as:

$$\mathbf{f}_i' = \begin{bmatrix} 1 & 0 \\ -\tan(\Delta\alpha_i + \Delta\beta_i) & 1 \end{bmatrix} \mathbf{f}_i^{\mathrm{T}} \quad (7)$$

where $\mathbf{f}_i' = [x', y']$ are the new coordinates of the i-finger contour, $\Delta\alpha_i$ is the offset angle of the i-finger and $(\cdot)^{\mathrm{T}}$ is the traspose.

ii) Shape: the shape shows slightly non-linear deformations motivated by the elasticity of the shape, the finger movement and the pressure applied during the acquisition. These changes are introduced in our model in two steps: i) the master hand-shape is modified introducing random noise in the vector of weights $\mathbf{b}' = \mathbf{b} + \Delta\mathbf{b}$, with $\Delta\mathbf{b}$ in the range $-0.15\sqrt{\lambda_k} \leq \Delta b_k \geq 0.15\sqrt{\lambda_k}$; ii) the finger movement itself introduces deformation in the joints between finger and palm. The continuity of the shape is guaranteed by interpolation of the coordinates which produces changes similar to those introduced by the elasticity of the skin.

Fig. 4 shows examples of synthetically generated multiple samples and real samples. The results show a natural variability including finger movement and small shape variations.

4. Evaluation of the Generation Model

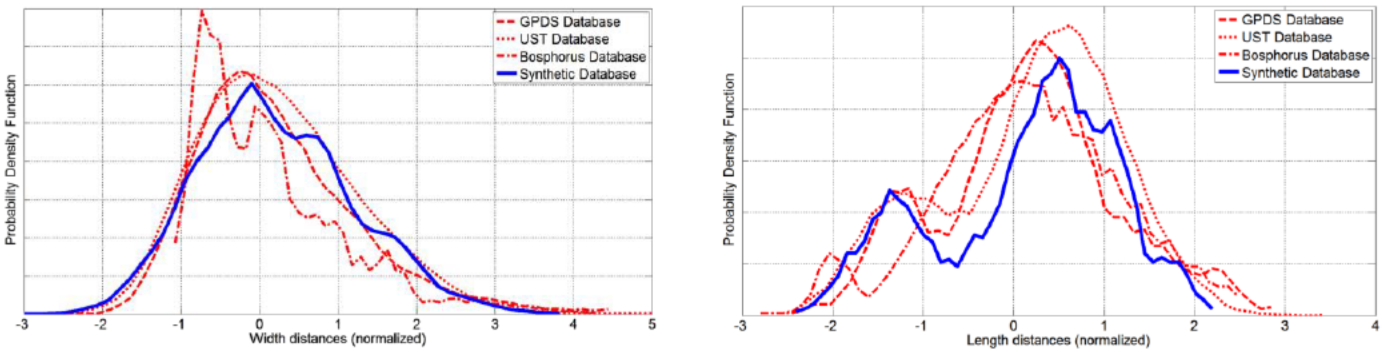
The procedure to evaluate the synthetic biometric samples generated with the proposed methodology is carried out to answer the following questions: How realistic are the synthetic images? Can they spoof a biometric recognition system? The first question is related with the visual realism of the samples and it comprises concerns about the natural aspect of the generated hand-shapes. The second question is a well-known procedure to establish the realism of biometric synthetic samples (Cappelli et al., 2007; Maltoni et al. 2009; Cappelli, 2009; Galbally et al., 2012b; Ferrer et al., 2014: Morales et al., 2014), and helps to measure the intra-person and inter-person variability of the generated samples and its usefulness in biometric applications.

The evaluation procedure is based on the exhaustive comparison between real data (from multiple public available databases) and a synthetically generated database.

4.1. Databases

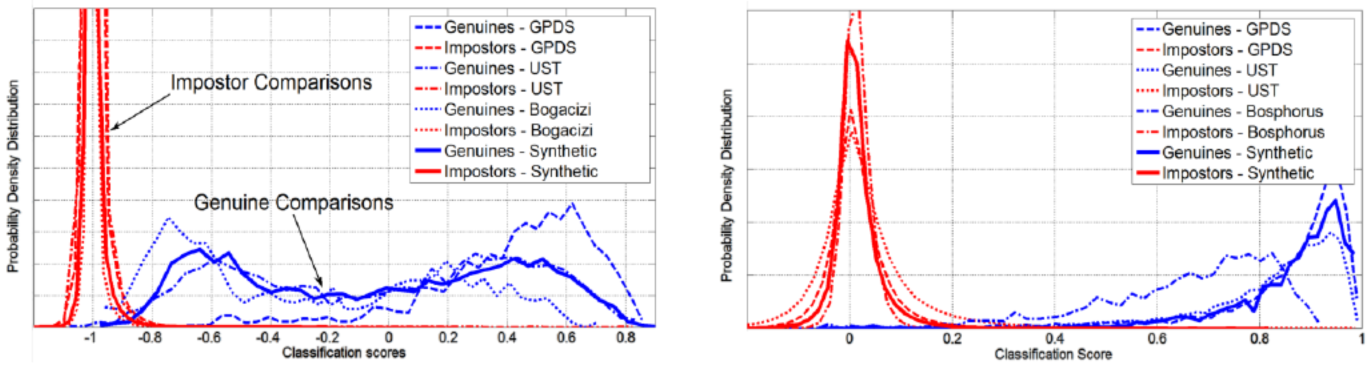
Traditional hand-shape approaches are based on CCD cameras or digital scanners, which provide images from which the hand-shape can be easily extracted, see (Wong et al., 2005) for a discussion of advantages and disadvantages between both acquisition methods. The synthetic hand-shape database is here compared with three public databases for hand-shape biometrics:

- **GPDSHand database:** this database includes 10 images from the right hand of 144 users (Ferrer et al., 2007) - captured using a digital scanner (acquired at 150 dpi).
- **Bosphorus database:** this database includes 3 images from right and left hand of 755 users (Yoruk et al., 2006) captured using a digital scanner (acquired at 150 dpi and reduced to 45 dpi via bilinear resizing).
- **UST database**: this database includes 10 images from



(a) (b)

Fig. 6: Widths (a) and lengths (b) from real (dashed and dotted lines) and synthetic (continuous lines) fingers. Zero mean and unit variance are enforced.



(a) (b)

Fig. 7: Score distributions for geometry-based (a) and global-appearance-based (b) hand-shape recognition methods.

right and left hand of 287 users (UST) captured using CCD camera (1280×960 pixels resolution).

- **Synthetic database:** a 10,000 × 5 hand-shape database (10,000 hands with five samples each) has been generated with the proposed methodology and used in the experiments reported in the following subsections.

4.2. Validation of the hand-shape biometrics

Traditional hand-shape recognition approaches are mainly based on the silhouette of the hand or features that can be derived from it such as sizes, distances, and angles. The finger morphology is one of the most discriminative aspects on the hands and Fig. 6 compares lengths and widths (one length and 12 widths for each finger) of synthetic and real fingers. The measures have been extracted according the method proposed in (Ferrer and Morales, 2011). Zero mean and unit variance are enforced to avoid scale distortions between samples from different datasets. This first result confirms that real and synthetic hand-prints exhibit similar geometric measures and therefore the generated hand shapes can be considered realistic.

As a further experiment, two hand-shape matching algorithms have been tested on synthetic and real hand-prints, then the corresponding match score distributions have been compared:

- **Geometric Features + SVM Classifier**: the first matching algorithm is based on finger geometry measures and LS-SVM classifier. The geometric features are obtained by measuring the widths and lengths of each finger (excluding the thumb finger because of its high variability). The feature vector is composed by 48 widths (12 per finger) and 4 lengths. The SVM classifier is trained according an open-set protocol which guarantee different users in training and test set. See (Ferrer and Morales, 2011) for a detailed description of the method.
- **Global Appearance + ICA2**: The silhouette of the hand contains much richer information than geometrical features. The second hand-shape matching algorithm is based on global silhouette matching based on pose-normalization and ICA2 algorithm. The authors provide freely the software implementing the approach proposed in (Konukoglu et al., 2006) which has shown competitive performances in publicly available databases (Dutağacı, et al., 2008).

Both algorithms are examples of two well-known hand-shape recognition strategies (Duta, 2006). While geometric features are related with the local information of the finger and palm, the ICA2 algorithm focus on the whole hand appearance. Fig. 7 shows the score distribution of real and synthetic databases for both algorithms, using two images as gallery set and the remaining as query set. In spite of the unavoidable differences among the scores distributions, it is quite evident that synthetic and real images lead to similar trends. This result suggests that the proposed synthetic hand-shape generation technique may be used for performance evaluation of hand-shape recognition methods.

5. Applications of Synthetically Generated Hand-Shape Databases

This work includes two applications of hand-shape synthetic samples which provide new insights into the hand-shape biometric recognition area.

5.1. Improving machine-learning classification methods

It is well-know that the availability of a large training set allows an effective training of machine-learning classifiers

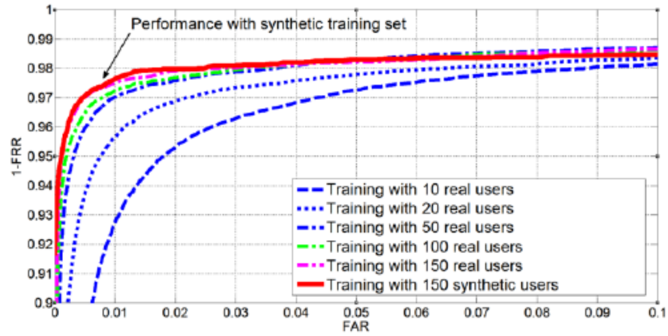


Fig. 8: ROC curves using Bosphorus database and finger geometry features.

(Bishop, 2006). This section proposes and evaluates the use of hand-shape synthetic images as training samples for hand geometry verification based on the Support Vector Machines algorithm (Ferrer and Morales, 2011). An experiment has been carried out on the Bosphorus database using the hand-shape matching algorithm based on geometry features and the SVM hand-geometry classifier described in *Section 4*. This particular database has been chosen because, with its 755 users, it was the largest available. The experiment has been carried out as follows: i) the SVM models corresponding to each subject have been trained using random training sets of 10, 20, 50, 100 and 150 people. The subjects chosen for the training stage have not been used in the verification phase (open-set paradigm); ii) each experiment has been repeated 20 times (introducing randomness in the training set selection) and its FAR and FRR curves have been averaged.

A similar experiment has been performed by using synthetic hand-shapes: i) the ASM-based hand-shape generator (described in *Section 3*) has been trained with 20 random users of the Bosphorus database (not used during the subsequent verification phase); ii) 150 synthetic subjects have been generated according the methodology proposed; iii) the synthetic users have been used as training set during the SVM training; here too, the experiment has been repeated 20 times. Fig. 8 shows the results obtained according to the training set size and the nature of the samples employed. The graph shows that by using only 20 users to synthesize a 150-subject training sets, it is possible to achieve results similar to those obtained with a training set of 150 real users. Table III shows the EER variance throughout the 20 runs of the experiment. The results suggest that by using synthetic training sets it is possible to train a classifier more robustly (i.e., in a way that is less dependent on a particular training set).

TABLE III. EER VARIANCE IN THE 20 RUNS OF THE EXPERIMENT

	Training set size (users)					
	10	20	50	100	150	Synthetic (150)
EER Variance	0.09	0.07	0.06	0.05	0.05	**0.01**
Max EER (%)	3.94	3.58	2.77	2.61	2.61	**2.23**
Min EER (%)	2.88	2.41	1.83	1.86	1.68	**1.99**

5.2. Scalability of hand-shape biometrics

Studying the scalability of biometric recognition techniques is an important and open topic. Unfortunately, the acquisition of large-scale datasets (millions of subjects) is very critical. For hand-shape biometrics, to the best of our knowledge, there is no public database larger than 800 users and the actual scalability of hand-shape approaches has not been proved yet. Therefore the generation of a large amount of synthetic images can be very useful in this context.

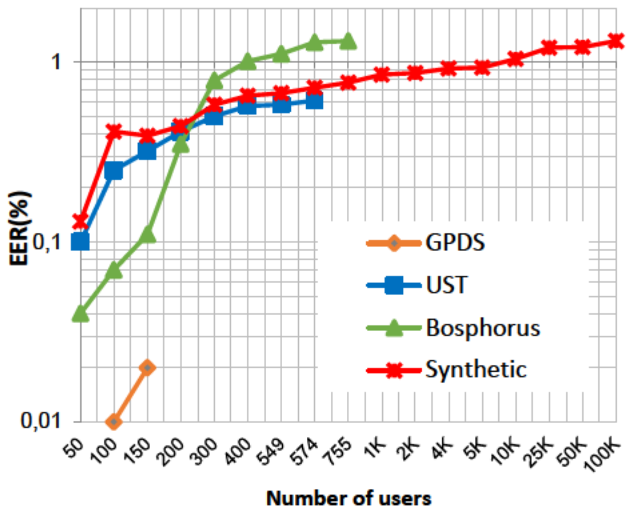


Fig. 9: EER (%) as a function of the number of users for the hand geometry verification approach in (Ferrer and Morales, 2011).

The methodology proposed in the present paper allows synthesizing large-scale datasets. A database of 100,000 × 5 hand-shape images has been generated and used for this experiment: two images have been selected for training and the remaining three for testing. Fig. 9 shows the results (see also and Table IV): all the real and synthetic databases show a similar trend when working with less than 1,000 users. The synthetic database makes it possible to predict what happens if the number of users is increased by two orders of magnitude. In particular, it shows that EER moves from 0.72% (for 574 users) to 1.31% for (100,000 users) suggesting that a good accuracy can be sustained by hand-shape verification approaches in large-scale scenarios.

All real and synthetic databases show a similar behavior although the different performances are produced most probably because of the different acquisition methodologies employed. While Bosphorus and GPDS databases were acquired using digital scanners (with deformation due to the pressure with the flat scanner) the UST database was acquired using a CCD camera without contact between the palm and any surface. Although the ASM was trained using GDSP database, the intra-class and inter-class variability introduced during the generation produces a distribution with a performance more similar to the UST database.

6. Discussions and Conclusions

This work has presented and analyzed a methodology for the generation of hand-shape images for biometric applications. The method proposed is divided in two main tasks: generation of master hand-shape images which deal with the inter-person variability and generation of multiple samples which deal with the intra-person changes. The realism of these synthetic images was assessed using both real and synthetic databases. The results evidence the realism of the synthetic samples generated by the proposed methodology and offers the possibility of generating a large scale dataset to use in biometric applications. Two novel applications using synthetic samples have been proposed and new ones could be proposed in the future using the 500,000 image database publicly available[3] for scientific purposes.

[3] http://atvs.ii.uam.es/databases.jsp

TABLE IV. EVOLUTION OF THE EER (%) WHEN THE NUMBER OF USERS INCREASES (TRAINING WITH 2 IMAGES)

	Databases			
	GPDS	UST	Bosphorus	Synthetic
People =>	150	574	755	10000
Hands =>	10	10	3	5
People	EER (%)			
50	0,00	0.1	0.04	0.13
100	0.01	0.25	0.07	0.41
150	0.02	0.32	0.11	0.39
200		0.41	0.35	0.44
300		0.50	0.79	0.58
400		0.57	1.01	0.65
574		0.61	1.29	0.72
650			1.33	0.76
755			1.31	0.77
800				0.83
900				0.84
1,000				0.85
2,000				0.87
3,000				0.89
4,000				0.92
5,000				0.93
10,000				1.04
25,000				1.20
50,000				1.21
100,000				1.31

Acknowledgment

A.M. is supported by a post-doctoral Juan de la Cierva contract by the Spanish MECD (JCI-2012-12357). This work has been partially supported by projects: BioSint (TEC2012-38630) and, Bio-Shield (TEC2012-34881) from Spanish MINECO, BEAT (FP7-SEC-284989) from EU.

References

Bishop, C. M., 2006. Pattern Recognition and Machine Learning. Springer.

Blanz, V., Vetter, T., 1999. A morphable model for the synthesis of 3D faces. In Proc. 26th Annu. Conf. Comput. Graph. Interact. Techn., pp. 187–194.

Cappelli, R., Maio, D., Maltoni, D., Wayman, J. L., Jain, A. K., 2006. Performance Evaluation of Fingerprint Verification Systems. IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 28, no. 1, pp. 3-18.

Cappelli, R., 2009. Synthetic fingerprint generation. In Handbook of Fingerprint Recognition, D. Maltoni, D. Maio, A. K. Jain, and S. Prabhakar, Eds. London, U.K.: Springer-Verlag, pp. 203–232.

Cardoso, L., Barbosa, A., Silva, F., Pinheiro, A. M. G., Proença, H., 2013. Iris biometrics: Synthesis of degraded ocular images. IEEE Trans. Inf. Forensics Security, vol. 8, no. 7, pp. 1115–1125.

Cootes, T. F., Taylor, C. J., Cooper, D. H., Graham, J., 1995. Active shape models - Their training and application. Computer Vision and Image Understanding, vol. 61, no. 1, pp. 38–59.

Duta, N., 2009. A survey of biometric technology based on hand shape, Pattern Recognition, vol. 42 pp. 2797–2806.

Dutağacı, H., Sankur, B., Yörük, E., 2008. A comparative analysis of global hand appearance-based person recognition. Journal of Electronic Imaging, vol. 17, no. 1, pp. 011018/1- 011018/19.

Feng, J., Zhou, H., Zhou, J., 2011. A preliminary study of handprint synthesis. In Proc. Chin. Conf. Biometric Recognition, pp. 133–140.

Ferrer, M. A., Morales, A., Travieso, C. M., Alonso, J. B., 2007. Low Cost Multimodal Biometric identification System Based on Hand Geometry, Palm and Finger Print Texture. In Proceedings of the 41st Annual IEEE International Carnahan Conference on Security Technology, pp. 52-58.

Ferrer, M. A., Diaz-Cabrera, M., Morales, A., 2014. Static Signature Synthesis: A Neuromotor Inspired Approach for Biometrics. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 37, no. 3, pp. 667-680.

Ferrer M.A., Morales, A., 2011. Hand-shape biometrics combining the visible and short-wave infrared bands IEEE Transactions on Information Forensics and Security, vol. 6, pp. 1305–1314.

Galbally, J., Fierrez, J., Martinez-Diaz, M., Ortega-Garcia, J., 2009. Improving the enrollment in dynamic signature verification with synthetic samples. In Proc. IAPR Int. Conf. Document Anal. Recognition, pp. 1295–1299.

Galbally, J., Plamondon, R., Fierrez, J., Ortega-Garcia, J., 2012. Synthetic on-line signature generation. Part I: Methodology and algorithms. Pattern Recognition, vol. 45, pp. 2610–2621.

Galbally, J., Fierrez, J, Ortega-Garcia, J., Plamondon, R., 2012. Synthetic on-line signature generation. Part II: Experimental validation. Pattern Recognition, vol. 45, pp. 2622–2632.

Galbally, J., Ross, A., Gomez-Barrero, M., Fierrez J., Ortega-Garcia, J., 2013. Iris image reconstruction from binary templates: An efficient probabilistic approach based on genetic algorithms. Computer Vision and Image Understanding, vol. 117, n. 10, pp. 1512-1525.

Gomez-Barrero, M., Galbally, J., Morales, A., Ferrer, M. A., Fierrez J., Ortega-Garcia, J., 2014. A novel hand reconstruction approach and its application to vulnerability assessment. Information Sciences, vol. 268, n. 0, pp. 103-121.

Jolliffe, I., 2002, Principal Component Analysis. Springer Verlag.

Kang W., Wu, Q., 2014. Pose-invariant hand shape recognition based on finger geometry. IEEE Transaction on Systems, Man and Cybernetics, vol. 44, no. 11, pp. 1510–1521.

Konukoglu, E., Yorük, E., Darbon, J., Sankur, B., 2006. Shape-Based Hand Recognition, IEEE Trans. on Image Processing, vol. 15, no. 7, pp. 1803-1815.

Maltoni, D., Maio, D., Jain, A. K., Prabhakar, S., 2009. Handbook of Fingerprint Recognition (Second Edition). Springer, London-Verlag.

Morales, A., Cappelli, R., Ferrer, M. A., Maltoni, D., 2014. Synthesis and Evaluation of High Resolution Hand-Prints. IEEE Transactions on Information Forensics and Security, vol. 9, no. 11, pp. 1922-1932.

Ortega-Garcia, J., J. Fierrez, F. Alonso-Fernandez, J. Galbally, M. Freire, J. Gonzalez-Rodriguez, C.Garcia-Mateo, J.-L.Alba-Castro, E.Gonzalez-Agulla, E.Otero-Muras, S.Garcia-Salicetti, L.Allano, B.Ly-Van, B.Dorizzi, J.Kittler, T.Bourlai, N.Poh, F.Deravi, M.Ng, M.Fairhurst, J.Hennebert, A.Humm, M.Tistarelli, L.Brodo, J.Richiardi, A.Drygajlo, H.Ganster, F.M.Sukno, S.-K.Pavani, A.Frangi, L.Akarun and A.Savran, 2010. The Multi-Scenario Multi-Environment BioSecure Multimodal Database (BMDB). IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 32, no. 6, pp. 1097-1111.

Plamondon, R., O'Reilly, C., Galbally, J., Almaksour, A. Anquetil, E., 2014. Recent Developments in the Study of Rapid Human Movements with the Kinematic Theory: Applications to Handwriting and Signature Synthesis. Pattern Recognition Letters, vol. 35, pp. 225-235.

Rabasse, C., Guest, R., Fairhurst, M. 2008. A new method for the synthesis of signature data with natural variability. IEEE Trans. Syst., Man, Cybern. B, Cybern., vol. 38, no. 3, pp. 691–699.

Sharma, S., Dubey, S. R., Singh, S. K., Saxena, R., Singh, R. K., 2015. Identity verification using shape and geometry of human hands. Expert Systems with Applications, vol. 42, pp. 821–832.

UST Hand Image Database, Department of Computer Science, The Hong Kong University of Science and Technology. (Provided by Dr. Helen Shen).

Venugopalan, S., Savvides, M., 2011. How to generate spoofed irises from an iris code template. IEEE Trans. Inf. Forensics Security, vol. 6, no. 2, pp. 385–394.

Wong, M., Zhang, D., Kong, W., Lu, G., 2005. Real-time palmprint acquisition system design. In Proc. of IEEE Vision, Image and Signal Processing, vol. 152, pp. 527-534.

Yoruk, E., Dutagaci, H., Sankur, B., 2006. Hand Biometry. Image And Vision Computing, vol. 24, no. 5, pp. 483-497.

Zhao, Q., Jain, A. K., Paulter, N. G., Taylor, M., 2012. Fingerprint image synthesis based on statistical feature models. Iin Proc. IEEE 5th Int. Conf. Biometrics, Theory, Appl. Syst. (BTAS), pp. 23–30.

Zhuoshi, W., Han, Y., Sun, Z., Tan, T., 2008. Palmprint image synthesis: A preliminary study. In Proc. 15th IEEE Int. Conf. Image Processing, pp. 285–288.