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Inverse Biometrics: A Case Study in Hand Geometry Authentication

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Abstract

Recently, a considerable amount of research has been focused on inverse biometrics, that is, regenerating the original biometric sample from its template. In this work, the first reconstruction approach to recover hand geometry samples from their feature vectors is proposed. Experiments are carried out on the publicly available GPDS Hand DB, where the method has shown a remarkable performance, after reconstructing a very high percentage of the hands included in the dataset. Furthermore, the proposed technique is general, being able to successfully reproduce the original hand shape sample regardless of the information and format of the template used.

1. Introduction

Automatic access of persons to services is becoming increasingly important in the information era. This has resulted in the establishment of a new technological area known as biometric recognition, or simply *biometrics* [7]. A biometric system is essentially a pattern recognition application that makes use of biometric traits (e.g., fingerprints, iris, face or hand images) to automatically recognize individuals.

After acquiring the biometric sample, these systems extract the intrinsic information which is discriminant and exclusive of that particular user. This information, or feature vector, is stored in a *biometric template* which is later used as a representation of the subject identity and deployed for authentication purposes. The biometric template should be a compact and precise representation of the user identity (e.g., iricode or minutiae points of a fingerprint). Therefore, one of the key aspects of the biometric recognition process to which

great efforts have been dedicated is the efficient “translation” of the raw biometric sample into a stable, simple and highly discriminant template.

However, over the last recent years important attention has also been paid to the opposite, and very challenging, reverse engineering problem: recovering the original biometric sample from its parameterized template. Such a reconstruction process has been generally referred to as *inverse biometrics* [9], and, for a long period of time it was believed to be unfeasible for certain traits such as the fingerprints or the iris.

In this context, several methods have been proposed for the reconstruction of face images [1], fingerprint impressions [2], or irides [8]. The reconstructed samples have been used for multiple applications such as vulnerability assessment, synthetically increasing the amount of data available for a certain user, or as a possible solution for privacy-related issues.

However, in spite of its many potential uses, the reverse engineering of biometric templates still remains unexplored for largely deployed traits such as the handwritten signature or the hand. In the present contribution we address the inverse biometrics problem for the hand geometry trait and propose the first reconstruction approach to recover hand geometry samples from their templates. The technique, which is based on a combination of the uphill-simplex algorithm and a synthetic hand generator, clearly shows the feasibility of such an inverse biometrics methodology. Furthermore, the proposed approach is general in the sense that it does not need to know the format of the template (i.e., what information is stored in it, or how it is stored).

The rest of the paper is structured as follows: in Sect. 2 the reconstruction method is presented. Afterwards the database and experimental protocols are described in Sect. 3. Experimental results are shown in Sect. 4 and final conclusions are drawn in Sect. 5.

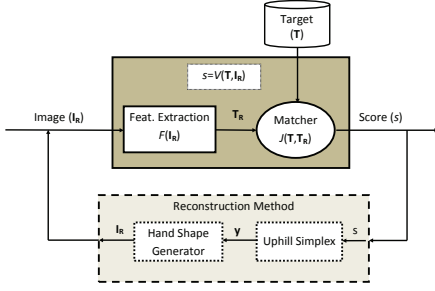


Figure 1. Diagram of the general structure of an image reconstruction method.

2. Reconstruction Method

Consider the problem of finding a real-valued matrix (in our case representing a hand geometry image) \mathbf{I}_R which, compared to an *unknown* template \mathbf{T} (related to a specific client), produces a similarity score bigger than a certain threshold δ , according to some unknown function \mathcal{V} , i.e.: $s = \mathcal{V}(\mathbf{I}_R, \mathbf{T}) > \delta$. The mapping function \mathcal{V} is internally divided into two other sub-functions, also unknown: $\mathbf{T}_R = \mathcal{F}(\mathbf{I}_R)$ extracts the features from the input image \mathbf{I}_R and obtains the corresponding template (\mathbf{T}_R), and $s = \mathcal{J}(\mathbf{T}_R, \mathbf{T})$ computes the similarity score between \mathbf{T}_R and the target template \mathbf{T} .

Let us assume that we have access to the evaluation of the function $\mathcal{V}(\mathbf{I}_R, \mathbf{T})$ for several trials of \mathbf{I}_R .

The problem stated above may be solved combining the hill-climbing based on the uphill simplex first presented in [6] and a generator of hand geometry images, according to the general diagram presented in Fig. 1.

The generator used to obtain the matrices \mathbf{I}_R (hand shape images) that will be compared with the target, T , is based on the Active Shape Model approach [3]. Starting from a previously aligned set of hand contours (with mean \bar{x}), PCA is applied to determine the k main directions of variation of the training set. A hand shape can then be generated as: $\mathbf{I}_R = \bar{x} + P\mathbf{y}$, where P is formed by the first k eigenvectors (with corresponding eigenvalues λ_k) of the covariance matrix, and $\mathbf{y} = [y_0, \dots, y_{k-1}]$ is the hand shape generating vector which will be optimized by the uphill simplex.

It has to be emphasized that the uphill simplex is not used to optimize the templates \mathbf{T} deployed by the system, but the feature vectors \mathbf{y} needed by the hand shape generator (which do not coincide with \mathbf{T}). This way, the proposed approach is general as it can be used to reconstruct the hand shape images independently of the template \mathbf{T} used by the system (e.g., size, format or in-

formation stored).

From a general perspective, the proposed reconstruction approach is as follows. Let us consider a simplex, that is, a polygon defined by $k + 1$ points \mathbf{y}_i in the k -dimensional space, obtained from randomly sampling a statistical model G . Each of these \mathbf{y}_i k -dimensional points (with $i = 1, \dots, k + 1$) is transformed into a hand geometry image \mathbf{I}_R using the hand shape generator. We iteratively form new simplices by reflecting one point, \mathbf{y}_l , in the hyperplane of the remaining points, in order to increase at each iteration the value of the mapping function \mathcal{V} . The point to be reflected will always be the one with the lowest score s , since it is, in principle, the one furthest from our objective. The algorithm stops when one of the \mathbf{I}_R^i images produces a score higher than the threshold δ .

In particular, the different steps followed by the reconstruction algorithm are:

1. Compute empirically the statistical model G .
2. Take $k + 1$ samples (\mathbf{y}_i) defining the initial simplex from the statistical model G and generate the corresponding matrices \mathbf{I}_R^i , with $i = 1, \dots, k + 1$, using the hand shape generator.
3. Compute the similarity scores $\mathcal{V}(T, \mathbf{I}_R^i) = s_i$.
4. Compute the centroid $\bar{\mathbf{y}}$ of the simplex as the average of \mathbf{y}_i .
5. Reflect the point \mathbf{y}_l according to the next steps, where the indices l and h are defined as:

$$h = \arg \max_i (s_i) \quad l = \arg \min_i (s_i)$$

- 5.a. **Reflection:** Given a constant $\alpha > 0$, the *reflection coefficient*, we compute:

$$\mathbf{y}_a = (1 + \alpha)\bar{\mathbf{y}} - \alpha\mathbf{y}_l.$$

Thus, \mathbf{y}_a is on the line between \mathbf{y}_l and $\bar{\mathbf{y}}$ being α the ratio between the distances $[\mathbf{y}_a\bar{\mathbf{y}}]$ and $[\mathbf{y}_l\bar{\mathbf{y}}]$.

Generate \mathbf{I}_R^a and compute $s_a = \mathcal{V}(\mathbf{T}, \mathbf{I}_R^a)$. If $s_l < s_a < s_h$ we replace \mathbf{y}_l by \mathbf{y}_a . Otherwise, we go on to step 5b.

- 5.b. **Expansion or contraction.**

- 5.b.1 **Expansion:** If $s_a > s_h$ (i.e., we have a new maximum) we expand \mathbf{y}_a to \mathbf{y}_b as follows:

$$\mathbf{y}_b = \gamma\mathbf{y}_a + (1 - \gamma)\bar{\mathbf{y}},$$

where $\gamma > 1$ is another constant called *expansion coefficient*, which represents

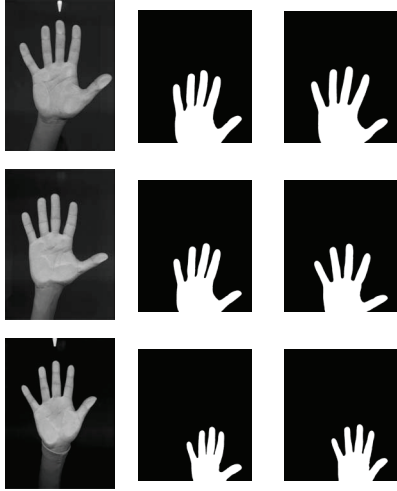


Figure 2. Typical hand images that can be found in the GPDS Hand DB (first column), with their corresponding reconstructions: without/with considering the finger lengths information (second/third columns).

the ratio between the distances $[y_b\bar{y}]$ and $[y_a\bar{y}]$.

Generate \mathbf{I}_R^b and compute $s_b = \mathcal{V}(\mathbf{T}, \mathbf{I}_R^b)$. If $s_b > s_h$, we replace y_l by y_b . Otherwise, we have a failed expansion and replace y_l by y_a .

- 5.b.2 **Contraction:** If we have reached this step, then $s_a \leq s_l$ (i.e. replacing y_l by y_a would leave s_a as the new minimum). Afterwards we compute

$$\mathbf{y}_b = \beta \mathbf{y}_l + (1 - \beta) \bar{\mathbf{y}},$$

where $0 < \beta < 1$ is the *contraction coefficient*, defined as the ratio between the distances $[y_b\bar{y}]$ and $[y_l\bar{y}]$.

Generate \mathbf{I}_R^b and compute $s_b = \mathcal{V}(\mathbf{T}, \mathbf{I}_R^b)$. If $s_b > \max(s_l, s_a)$, then we replace y_l by y_b ; otherwise, the contracted point is worse than y_l , and for such a failed contraction we replace all the y_i 's by $(y_i + y_h)/2$.

6. With the new y_l value, update the simplex and return to step 4.

The hill climbing algorithm stops when $s_h \geq \delta$ or when the maximum number of iterations is reached.

Without lengths		With lengths	
SR	N_{it}	SR	N_{it}
60.03%	105.66	70.12%	119.8

Table 1. Reconstruction performance for the two types of templates.

3. Database and Experimental Protocol

The reconstruction method described in Sect. 2, is used to recover the hand shape images from the GPDS Hand database¹. This dataset comprises 144 users with 10 images per user, acquired with a commercial scanner of 150 dpi. Some typical samples that may be found in the database are shown in Fig. 2 (first column).

Hand-shape recognition approaches have been traditionally based on geometry and appearance features [4]. In the present contribution, the evaluation experiments were carried out using the hand shape geometrical-based system described in [5] which considers two types of templates (\mathbf{T}), namely: *i*) templates with information related to the finger lengths, and *ii*) templates with no data on the finger lengths. For each user, and for the two scenarios, a hand shape image is reconstructed with the algorithm described in Sect. 2. Examples of the reconstructed images obtained for different users under both scenarios can be seen in Fig. 2 (columns two and three).

4. Results

As a first step, exhaustive development experiments were carried out to determine the two initialization parameters: *i*) the dimensionality (k) of vectors \mathbf{y} , which was finally set to $k = 50$; and *ii*), the statistical model G , which was defined as a uniform distribution within the limits $[-3\sqrt{\lambda_k}, -3\sqrt{\lambda_k}]$, being λ_k the eigenvalue corresponding to the k_{th} eigenvector of matrix P .

As mentioned before, two sets of evaluation experiments were carried out, one for each type of template considered, in which the samples comprised in the GPDS Hand DB were reconstructed. The threshold δ (i.e., score value where a hand shape image is considered to have been successfully reconstructed) was fixed at an operating point corresponding to a False Acceptance Rate (FAR) $< 0.1\%$. The experimental results are shown in Table 1, from which different observations may be extracted:

¹Publicly available at <http://www.gpds.ulpgc.es/download/index.htm>

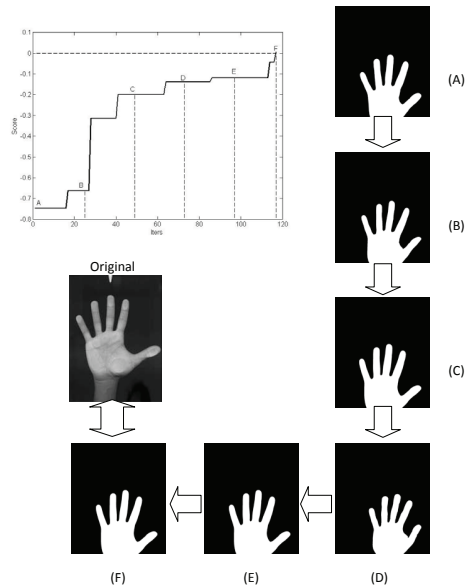


Figure 3. Evolution of the score and the synthetic hand shapes for a successfully reconstructed hand shape.

1. The evaluation clearly shows the feasibility of recovering the original hand shape image from its template, with a percentage of successfully reconstructed hands (SR) of 65% on average for the two scenarios considered.
2. The SR increases from 60.03% for the first type of templates considered (without lengths information), to 70.12% for the second type of templates (where the lengths are taken into account) at the cost of needing only 14% more iterations (N_{it}) on average. This means that templates with more information can improve the system performance, but also may help to recover the original hand geometry sample.
3. The results point out the generality of the proposed approach and its ability to reconstruct the hand shape regardless of the information stored in the templates \mathbf{T} (in this case, with and without the finger lengths data).

In Fig. 3 the evolution of the score for a successful reconstruction under the second scenario is depicted, together with the hand shapes obtained at several iterations (marked with letters A to F) and one of the images of the target user. Starting from a random hand, the algorithm is able to adapt it to the user's shape, until the threshold δ is reached (marked with a dashed line).

5. Conclusions

The inverse biometrics problem has been addressed for the hand-geometry trait. In this context, the first method for the reconstruction of the original hand shape images from their templates has been presented. Experimental results have shown the high potential of the approach, where over 70% of the hands in the database were successfully reconstructed, thus proving the efficiency of the proposed method.

Furthermore, the proposed reconstruction technique has shown a high degree of generality, being able to recover the hand geometry images from different types of templates (in terms of format and information stored).

Inverse biometrics methods such as the one proposed in the present contribution may have many different potential applications such as synthetically increasing the available data of a given user or for vulnerability assessment purposes.

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