H

Hand Shape

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Synonyms

Hand contour

Definition

A hand shape biometric system uses a camera or scanner-based device to acquire the hand image of a person from which shape information is extracted and compared against the information stored in a database to establish identity. Due to its limited discrimination power, a hand shape biometric system mostly operates in verification mode; that is the system *confirms or negates* the claimed identity of an individual.

Introduction

An increasing number of systems require positive identification before allowing an individual to use their services. Biometric systems are already employed in domains that require some sort of user verification. It is generally accepted that fingerprint and iris patterns can uniquely define each member of an extremely large population which makes them suitable for large-scale recognition (establishing a subject's identity). However, in many small-population applications, because of privacy or limited resources, it is only needed to authenticate a person (confirm or deny the person's claimed identity). In these situations, traits with less discriminating power such as hand shape, hand geometry, voice or signature can be used.

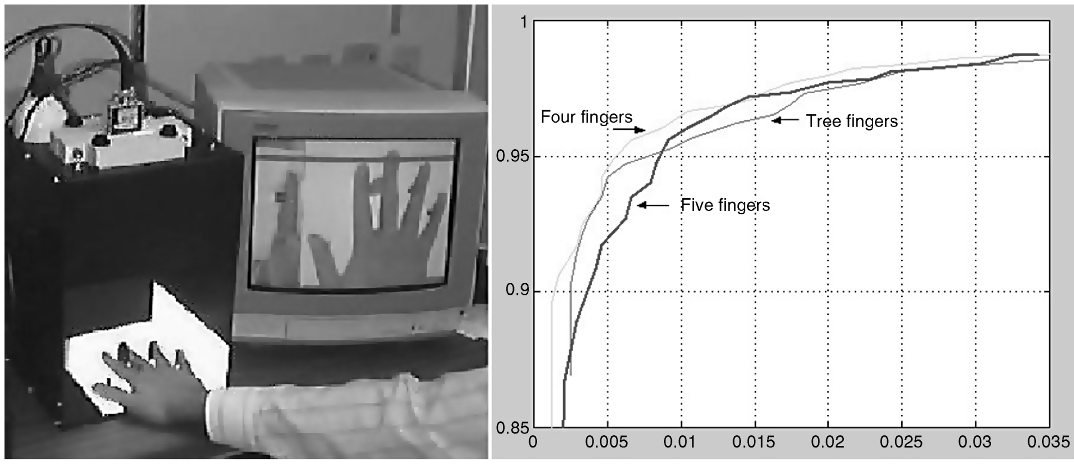
As noted in [1], hand shape-based authentication is attractive due to the following reasons:

1. Hand shape can be captured in a relatively user convenient, nonintrusive manner by using inexpensive cameras.
2. Extracting the hand shape information requires only low resolution images, and the user templates can be efficiently stored (120-byte templates are reported in [1]).
3. This biometric modality is more acceptable to the public mainly because, it lacks criminal connotation.
4. Additional biometric features such as hand geometry, palmprints, and fingerprints can be easily integrated to an existing hand shape-based authentication system.

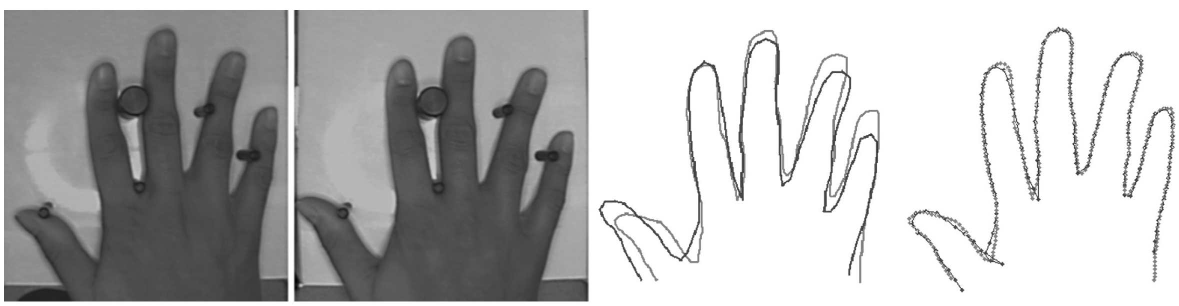
Operation of a Hand Shape-Based Biometric System

A hand shape-based biometric system operates according to the general diagram in [2] Fig. 2. In the enrollment stage, hand shape data is acquired from the registered users, feature sets are extracted from the acquired data, and one or multiple templates per individual are computed and stored in a database. In the deployment stage, one snapshot of the user's hand is captured; a feature set is computed and then compared to the user's templates in the database. Based on the comparison result, the claimed identity is accepted or denied. As described in [2], the system comprises the following modules: the sensor module, the feature extraction module, the matching module, and the decision-making module. Au1

The sensor is usually a low/medium resolution CCD camera attached (beneath or above) to a platform on which the hand is placed (Fig. 1a). Some multimodal biometric systems capture the palm surface which includes both the hand shape and palmprints



Hand Shape. Figure 1 (**a**) Example of a hand shape image acquisition system. (**b**) ROC curves for a hand shape-based verification system. The three curves correspond to feature vectors extracted from three, four and five fingers.



Hand Shape. Figure 2 Hand shape alignment. Two scans of the same hand: (**a**–**b**) original images, (**c**) hand shapes extracted from (**a**) and (**b**) overlaid, and (**d**) finger aligned shapes (Mean alignment error = 2.20 pixels).

[3]. Other systems capture the dorsal surface of the hand from which only the hand contour can be extracted (Fig. 2, [1, 4, 5]). Some of the systems include on the platform 4–6 pegs to guide the placement of the user's hand [4, 5]. Several researchers noted that the guidance pegs deform the hand contour and decrease user convenience and proposed peg-less setups [1, 3, 6]. In a few systems, the sensor consisted of a 45 dots per inch (DPI) scanner [3, 6].

In the feature extraction module, a set of discriminating features is computed from a user's raw hand image(s). The hand images are first pre-processed in order to extract the hand contour and eliminate artifacts such as the guidance pegs, user rings, overlapping cuffs, or creases around the contour due to too light or too heavy hand pressing. The pre-processing step can range from simple ▶ thresholding [1, 5] to sophisticate gray-level segmentation (▶ Image segmentation) [4]. Possible dents at the artifact location are smoothed by linear interpolation [4, 5] and/or morphologic operators [3].

In order to properly compare feature vectors extracted from hand images, one has to align the hand contours such that each feature is computed from the same region of the hand. Most of the older systems relied on the pegs to align the hand images. However, if the user is untrained or does not cooperate to proper use of the hand scanner, then the resulting images are not aligned (Fig. 2(c)) and the system's verification performance degrades [4]. Therefore, it is necessary to automatically align the acquired hand shapes before extracting the feature vectors used for verification. Due to the flexible nature of the palm and fingers, there may be no linear transformation which accurately aligns two hand contours. Hence, many of the proposed alignment procedures detect and align each finger separately. The simplest finger alignment method consists in registering the fingertip, the two adjacent valley points and several equally spaced points along the contour in between the three landmarks [5]. Similarly, a translation, rotation, and scaling can be found to align the finger with symmetry axis [6]. A more sophisticated alignment procedure (based on quasi-exhaustive polynomial search of point pair matching between two sets of contour points) is presented in [4]. This procedure has the advantage of always finding a good alignment even if the valley-point landmarks are not accurately detected. The alignment step can be avoided if the set of features extracted from the hand image is invariant to Euclidean transformations [1].

The hand shape can be modeled either explicitly as a set of 2D coordinates of several landmark points along the hand contour [4, 5] or implicitly as a binary image of the hand over an empty background [1, 6]. The two representations are intrinsically equivalent; each of them can be easily derived from the other. With both representations, dimensionality reduction procedures may have to be applied as the original data typically has a high dimensionality (see the fifth column in Table 1). The dimensionality reduction methods most used are ▶ principal component analysis (PCA) and independent component analysis (ICA), and are applied to either the original data or to a transformed version of the data (e.g., the Zernike moments in [1]).

One or several templates per user may be created during the enrollment stage and stored in the system's database. The templates are either the raw feature vectors computed from a user's hand images or the average of those feature vectors.

The matching module compares a user feature vector against the user's template(s) stored in the database in order to generate matching scores. Since the feature vectors are usually points in an N-dimensional Euclidean space, any metric distance can be used for computing a matching score: Euclidean distance [1], ▶ Mahalanobis distance, absolute (L_1) distance [6], correlation coefficient, etc. A few studies explicitly model the class-conditional probabilities under Gaussian assumptions [5]. As an exception, [3, 4] ▶ Procrustes shape distance can be used since the feature vectors are shapes corresponding to the hand contour. The matching score is a positive number which shows the dissimilarity between the user's hand and the templates in the database.

The final decision concerning the user's identity (identification) or the user's claimed identity (verification) is taken by the decision module. In verification mode, the decision is typically threshold based: if the matching score is below a given threshold the claimed identity is accepted, otherwise it is rejected. The threshold value is chosen based on the system's ROC curve such that the system satisfies some operating constraints (e.g., an upper bound on the false accept rate, an equal error rate, etc.). In identification mode, the incoming feature vector is typically assigned the identity of the closest database template if the distance to that closest template is lower than the verification threshold, otherwise the feature vector is considered to belong to an imposter.

Hand Shape. **Table 1** Comparison of some hand shape-based systems presented in the literature

System	Population size	Samples/ person	Number/ type of templates	Features used	Similarity measure	Performance
[1]	40	10	5 (raw feature vectors)	Zernike moments of the binary hand image followed by PCA (30)	Euclidian	FAR = 0.01 FRR = 0.02 EER = 0.0164
[2]	53	2–15	1–14 (raw contours)	Hand contour coordinates (120–350 contour points)	Mean alignment error	FAR = 0.01 FRR = 0.06
[4]	51	10–20	1 (average) + multiple raw	Hand contour coordinates, angles (51–211 contour points)	Log-Likelihood under Gaussian assumption	EER = 0.00001 – 0.002
[5]	458	3	2 (raw feature vectors)	Contour coordinates (2048 points) ICA on binary hand image (458)	Modified Hausdorff L1, cosine distance	EER = 0.01– 0. 02

Performance Evaluation

For most of the research systems, performance evaluation can only be based on the results and comparisons provided by their authors. Several enrollment and performance evaluation methodologies are discussed in [5]. If extensive enrollment data can be acquired, best performance is attained when an average template is computed from each user's enrollment measurements. However, such a system is less user-friendly and more difficult to deploy. A more realistic deployment scenario requires only one or few enrollment measurements per user. In such case, a template may actually be a raw feature vector and the main system parameter to estimate is the decision threshold. Most researchers split the available measurements for each user into an enrollment set and a testing set, and evaluate the threshold value based on the enrollment data. This has an advantage that the training data is representative for the test data, i.e., one expects to obtain an estimate of the decision threshold which works as well on the test data. In commercial deployments though, the system may be trained by the manufacturer while the enrollment is performed by the customer who has to use the factory set threshold.

It is difficult to directly compare the performance figures reported in the literature. The main reason is the absence of (1) a common benchmark data set and (2) standard enrollment and testing procedures. The different datasets used for research introduce several variation factors in the systems reported: (1) population size, (2) population age and/or structure, and (3) users' motivation to cooperate. Table 1 summarizes the performance of some research systems tested in identity verification mode. Some authors only report equal error rate (EER) figures while others include the system ROC curve. When the ROC curve was present, the estimated FRR rate corresponding to FAR = 0.01. As it can be seen in the last column of Table 1, most systems reported error rates on the order of 10^{-2}. A few systems have also been tested in identification mode and report identity recognition errors of 1–3% [6]. Note that no separate imposter population is used so the recognition error may be under estimated. Some authors integrate hand shape features with palm-based features (which can be acquired through a single image measurement) and report verification error rates on the order of 10^{-3} [3].

Limitations of the Hand Shape-Based Biometric Systems

There are two factors which make a hand shape-based biometric system less accurate than a fingerprint or iris-based system [4]:

1. The hand shape is not unique within a large population. That is demonstrated in Fig. 3: after finger alignment, the hand contours of two different users are almost identical. Therefore any geometric features extracted from the two aligned contours will be very similar and the system will likely confuse the identity of the two persons. In [4] three pairs of users with very similar hand shapes within a population of 53 persons were identified. However, the problem is alleviated if the system is used in verification mode since an imposter is less likely to know the identity of the registered user(s) whose hand shape best matches his or hers.
2. The human hand is a flexible object and its contour may suffer non-linear deformations when multiple hand images are acquired from the same person.

Hand Shape. Figure 3 Hand shape alignment. Two scans of different hands: (**a**–**b**) original images, (**c**) hand shapes extracted from (**a**) and (**b**) overlaid, and (**d**) finger aligned shapes (Mean alignment error = 2.02 pixels).

That is demonstrated in Fig. 2 where a user's thumb appears to be longer in one of the images, a fact which makes the system reject its true identity. This problem is alleviated if the thumb (which can deform more than the other four fingers) is excluded from the feature vector calculation. Figure 1(b) compares the ROC curves corresponding to using all five fingers versus excluding the thumb and/or the little finger. The system which excludes the thumb exhibits a substantially better performance over the system which uses all five fingers.

Summary

Hand shape-based biometric systems have been successfully demonstrated for applications involving personal identity verification. Their ease of use, nonintrusiveness, public acceptance, integration capabilities, and small resource requirements have made hand shape popular among the different biometric modalities.

Related Entries

- ▶ Hand geometry
- ▶ Independent Component Analysis
- ▶ Multimodal systems
- ▶ Palmprint matching

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