DEFORMABLE MATCHING OF HAND SHAPES FOR USER VERIFICATION

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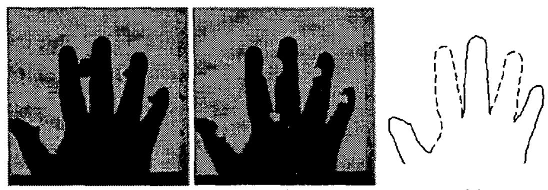
ABSTRACT

We present a method for personal authentication based on deformable matching of hand shapes. Authentication systems are already employed in domains that require some sort of user verification. Unlike previous methods on hand shape-based verification, our method aligns the hand shapes before extracting a feature set. We also base the verification decision on the **shape distance** *which is automatically computed during the alignment stage. The shape distance proves to be a more reliable classification criterion than the handcrafted feature sets used by previous systems. Our verification system attained a high level of accuracy: 96.5% genuine accept rate vs. 2% false accept rate. This performance is further improved by learning an enrollment template shape for each user.*

1. MOTIVATION

Automatic human identification has become an important issue in today's information and network based society. The techniques for automatically identifying an individual based on his physical or behavioral characteristics are called biometrics. Biometric systems are already employed in domains that require some sort of user verification (e.g., for access control or welfare disbursement programs). Numerous distinguishing traits that have been used for personal identification include fingerprints, face, voice, iris and hand geometry. 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 applications, because of privacy or limited resources, we only need to authenticate a person (confirm or deny the person's claimed identity). In these situations, we can use traits with less discriminating power such as voice or hand shape.



(a) (b) (c)

Figure 1: Hand shape extraction. (a) Gray scale (480 × 485) image captured by a hand scanner; (b) Peg removal; (c) Hand contour extraction and finger separation (we use continuous and dashed lines to separate the five sets of points denoting the five fingers).

Hand geometry-based verification systems have been commercialized for almost three decades. Still, their technical descriptions are scarce and the available informations is based mostly on patents (see [1, 2] and the references therein). However, the problem of matching hand shapes is not only important for biometric systems, but it is part of a more general, shape-based object learning and recognition topic (see for example studies by Grenander *et al.* [3] and Hill *et al.* [4]). We propose to approach the practical problem of person verification using the powerful tools of deformable shape analysis. This is motivated by the limited ability of the hand shape acquisition system to implicitly register different hand images using the rigid pegs on the hand scanner platen (Fig. 1(a)). If the user has not been properly trained or does not cooperate to properly use the hand scanner, then the resulting images are not aligned (Fig. 2(c)) and the system's verification performance degrades [1, 2]. Therefore, it is necessary to align the acquired hand shapes before extracting the feature vector used for verification. On the other hand, it is also useful to compare the discriminating power of the handcrafted feature set used by the existing systems to that of the

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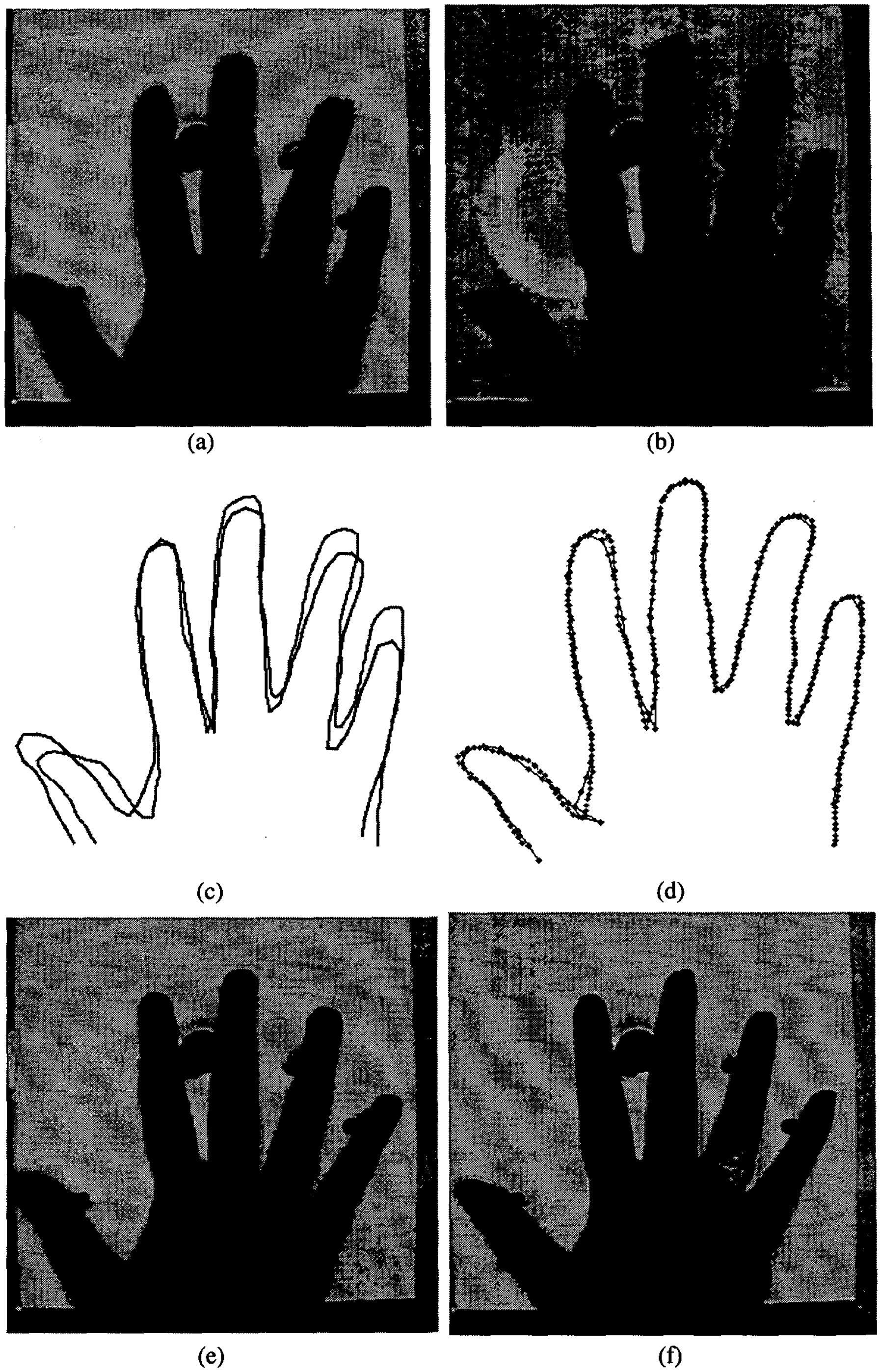
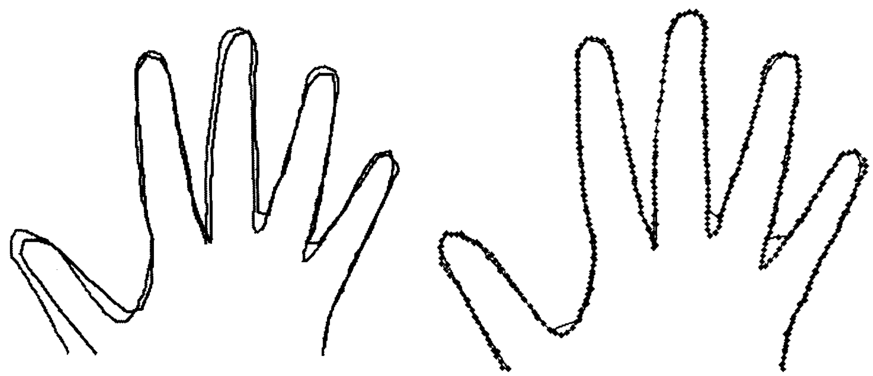


Figure 2: Hand shape alignment. Two scans of the same hand: (a)-(b) original images, (c) hand shapes extracted from (a) and (b) overlaid, and (d) aligned shapes (Mean alignment error = 2.20). Two scans of different hands: (e)-(f) original images.



(g) (h)

Figure 2: Hand shape alignment (continued). Two scans of different hands: (g) hand shapes extracted from Fig. 2 (e) and (f) overlaid, and (h) aligned shapes (Mean alignment error = 2.02). Notice that although the two shapes come from different hands, they are almost identical.

shape distance between two hand shapes which is a byproduct of our alignment procedure.

2. PROPOSED METHOD

Given a pair of top views of hand images acquired by a hand scanner similar to those described in [1, 2], we propose the following hand shape matching paradigm:

1. *Peg removal.* A mask containing the known positions of the five pegs is used to replace the pegs with a background like color (Fig. 1(b)).
2. *Contour extraction.* A *mean-shift* unsupervised segmentation [5] is applied to each image and a contour following algorithm is used to compute the shape of the hand (Fig. 1(c)).
3. *Finger extraction and alignment.* The five pairs of corresponding fingers are extracted from each contour and aligned separately with respect to the rigid transformations group as described in Section 3. We chose to align pairs of fingers as opposed to the entire hand because of the following reasons: (i) a human hand is an articulated object and the motion of one finger cannot be described by a linear transformation, but rather by a set of local rigid transformations and small deformations, (ii) Computationally, it is faster to detect and align individual fingers than an entire hand.
4. *Pairwise distance computation.* Each alignment in Step 3 produces a set of point correspondences (Figs. 2(d) and (h)). The *Mean Alignment Error* (MAE) between the two hand shapes is defined as the average distance between the corresponding points.
5. *Verification.* A pair of hand shapes is said to belong to the same hand if their MAE is smaller than a threshold T. Usually, the Neymann-Pearson rule that minimizes the False Reject Rate (FRR) for a fixed False Accept Rate (FAR) is employed to compute T.

3. HAND SHAPE ALIGNMENT

We represent the shape of a hand by a set of *ordered* points in the Euclidean plane. Most studies dealing with shapes generally agree that if D is a "distance" function between two sets of points A and B, then the point set B is *aligned* to the point set A with respect to a transformation group G (e.g., rigid, similarity, linear, affine) if $D(A, B)$ cannot be decreased by applying to B a transformation from G. We use a least-squares type distance because it provides a convenient way to define a prototype from a set of simultaneously aligned shapes (Procrustes analysis [6, 7]) and, once the point correspondences are found, there exists an analytical (exact) solution to the alignment problem [8]. However, in order to use a least-squares alignment method one should know point correspondences between the two sets. Most of the time, the point sets are automatically derived from images, so there are no known correspondences between them. Moreover, some points may have no correspondence so they should be considered as outliers. In practice, point correspondences have been obtained by a painstakingly manual inspection of the data. To automatically find point correspondences between two hand shapes, we separately aligned each pair of corresponding fingers based on quasi-exhaustive polynomial search of point pair matchings between the two sets of points (described in detail in [7]). From an initial (partial) hypothesis (that is, a pair of points from A matched into a pair of points from B), a complete hypothesis (match matrix) is generated and verified by applying to B the similarity transformation computed from the partial hypothesis and applying a step of the ICP algorithm [9].

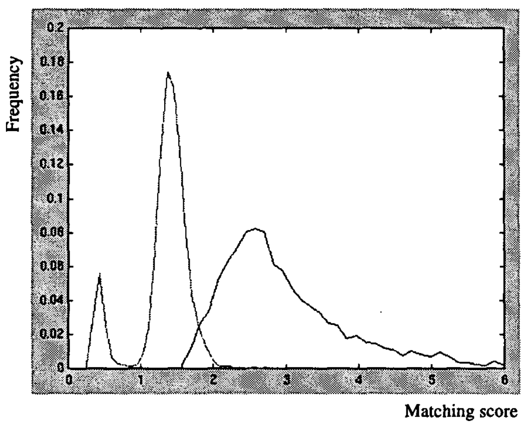


Figure 3: Mean alignment error distributions for the genuine class (left) and imposter class (right). The distributions are derived based on a total of 353 hand images of 53 persons.

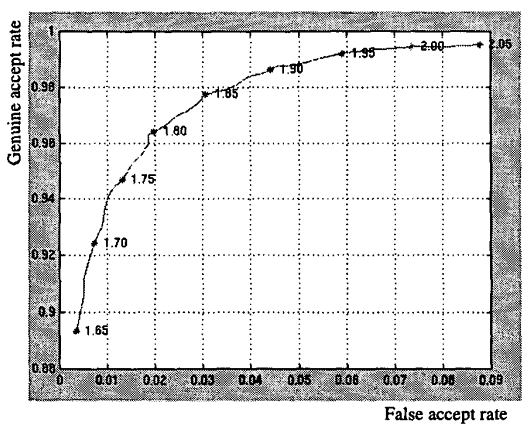


Figure 4: ROC curve for the hand shape-based verification system. The annotations on the curve represent different thresholds on the MAE distance.

4. EXPERIMENTAL RESULTS AND DISCUSSION

A data set of 353 images of 53 persons was collected (the number of images per person varied between 2 and 15). We show the alignment of two hand shape pairs in Fig. 2, the first pair belongs to the same hand while the second pair is formed by different hands. In each pair, one of the hand shapes contains about $120-130$ points, while the other contains about $300-350$ points (see [7] for details about the number of points to be used). To each pair of images of the same hand, we applied Steps 1-5 of the algorithm in Section 2 and obtained a complete set of 3,002 intra-class pairwise distances. We also randomly chose a set of 3,992 pairs of images of different hands and obtained a set of inter-class distances. Based on these distance sets, we computed the distributions of the genuine and imposter classes (Fig. 3). One can see that the two distributions are very well separated. Moreover, the right tail of the genuine distribution that overlaps the imposter distribution is generated by the images where the subjects did not properly place their hand on the scanner. Such an example is shown in Fig. 2(b). We also noticed that the left tail of the imposter distribution that overlaps the genuine distribution is generated by the images where different subjects have almost identical handshapes. Such an example is shown in Fig. 2(e)-(f).

The *ROC* curve associated with the two distributions is shown in Fig. 4. One can see that the classification system is very accurate: e.g, for a threshold $T = 1.80$ the genuine accept rate is 96.5% for a 2% false accept rate. Although the 2% false accept rate may seem high, in practice, it is much smaller, since a user of the system does not know the identity of which other user he can assume such that their hand shapes match. The genuine reject rate of the system can also be decreased by learning an enrollment template (average) shape for each user as described in [7]. We believe that the performance of our verification system is comparable to the state-of-the-art commercial systems. We also emphasize that after alignment, one does not need to compute a traditional set of handcrafted features anymore. One can simply use the MAE criterion whose value is available once the alignment is done. The alignment time for a pair of hand shapes is about 2 seconds on a 250 MHz Sun Ultrasparc.

Acknowledgments

We would like to thank Arun Ross of MSU and Dr. Sharath Pankanti of IBM T. J. Watson Research Center for data collection and to Dorin Comaniciu of Rutgers University for the mean-shift segmentation code.

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