PERSON AUTHENTICATION BASED ON HAND SHAPE

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ABSTRACT

A system has been developed for person identification based on hand images. The images of the left hand of the subjects are captured by a flatbed scanner in an unconstrained pose. The silhouettes of hands are registered to a fixed pose, which involves both rotation and translation of the hand and, separately, of the individual fingers. Independent component features of the hand silhouette images are used for recognition. The classification performance is found to be very satisfactory and it is shown that, at least for groups of one hundred subjects, hand-based recognition becomes a viable and secure access control scheme.

1. INTRODUCTION

Biometric technologies use physiological and behavioral traits of individuals to identify them. The personal features used in a biometric identification scheme can be physiological, such as facial features, fingerprints, iris, retinal scans, hand and finger geometry; or behavioral, such as voice print, gait, signature, and key stroking.

In this study, we develop a biometric scheme based solely on hand shape. We conjecture that hand shape could be a simple and robust alternative for person recognition in access control applications. Hand image can be captured with a flatbed scanner and this style of sensing already obviates some of the ambiguities associated with, for example, face images, which are subject to pose, expression and lighting variations, as well as environmental factors, like interferences, in voice-based recognition. Therefore, authentication based on hand shape can be an attractive alternative due to its unobtrusiveness, low-cost and easy interface, and low data storage requirements.

Previous hand-based authentication schemes in the literature have utilized hand features and/or palm print data. For example the authors in [10, 8] and [6] extract certain geometrical attributes from the hand contour, such as width and length of fingers, size of the palm and the ratio of palm with respect to fingers. In the identification stage, these

geometrical feature vectors, constituted from these measurements, are compared using Euclidean and Hamming distances. Other schemes are based on palm prints [4], [11], where, hands are registered with respect to the life and heart lines and then compared based on corresponding straight-line approximations in each hand.

In our paper we use purely hand-shape information for person recognition. The algorithm preprocesses the acquired image, by first segmenting and then normalizing it for hand's varying posture and deformable shape. The "hand normalization" involves the registration of the whole hand as well as individual rotations of the fingers to standard orientations. Subsequently, hand recognition is based on the comparison of the features extracted from the normalized images.

The paper is organized as follows. In Section 2 the segmentation of hand images are presented. The normalization steps for the deformable hand images are given in Section 3. Feature extraction and classification results are discussed in Section 4 and 5. Conclusions are drawn in Section 6.

2. HAND SEGMENTATION

Although hand segmentation may seem to be a straightforward task, segmentation accuracy may suffer from artifacts due to rings, overlapping cuffs or wristwatch belts/chains, or creases around the borders from too light or heavy pressing. Furthermore, the delineation of the hand contour must be very accurate, since the differences between hands of different individuals are often very small. We have comparatively evaluated two alternate methods of segmentation, namely, clustering followed by morphological operations and the watershed transform-based segmentation [9]. Both schemes are adequate for removing ring artifacts and in yielding accurate contours.

3. NORMALIZATION OF HAND CONTOURS

The normalization of hand images is the most critical operation for a hand-shape based biometry application. It involves registration of hand images by global rotation and translation, as well as re-orienting fingers individually along standardized directions, without causing any shape
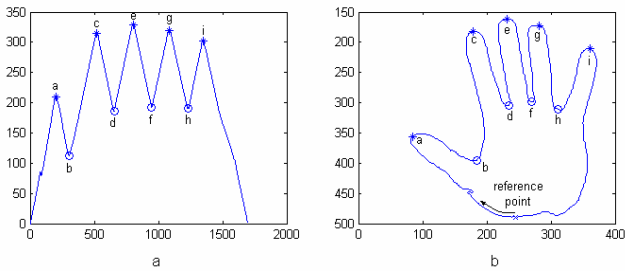
Figure 1: a) Radial plot of hand contours; b) Hand extrema

distortions. The necessity of finger re-orientation is illustrated in Fig. 2b. This figure shows two hand images of the same person taken in different sessions. Notice that even after global registration along the direction of the larger eigenvector, hands do not match exactly. In fact, such intra-differences can easily eclipse inter-differences and obfuscate recognition. Hence it is necessary to set the fingers to standard orientations before feature extraction.

The processing steps for hand normalization are as follows:

3.1 Localization of Hand Extremities

A robust technique for determining the tips of fingers and the bottom of the inter-finger valleys is provided by the radial plot where the origin is taken inside the hand and sufficiently close to the wrist. We took this reference point as the intersection of the major axis (the larger eigenvector of the inertial matrix) with the wrist line. The resulting radial sequence yields minima and maxima corresponding to the sought nine extremum points. The resulting extrema (Fig. 1a) are very stable since the definition of the 5 maxima (fingertips) and 4 minima (inter-finger valleys) are not affected by the contour noise.

3.2 Finger Registration

The hand normalization algorithm consists of the following steps (see Fig. 2):

a) Finger extraction: We extend segments from the tip along the finger side toward the two adjacent valley points. The shorter of these two segments is chosen, and then it is swung like a pendulum towards the other side. This sickle sweep cuts neatly the finger and its length can thus be computed (Fig. 2a).

b) Finger pivots: Fingers rotate around a joint, which is located between proximal phalanx and the corresponding metacarpal bone. Therefore the major axis of each finger is prolonged toward the palm by 20% in excess of the corresponding finger length (determined in part a), as shown in Fig. 2a. The ensemble of end-points of the four fingers axes (index, middle, ring, little) is critical for determining the scale and orientation of the whole hand.

c) Hand pivotal axis: A pivot line is created, which passes either through these four points by least squares fitting or simply through joining together the pivots of the index and
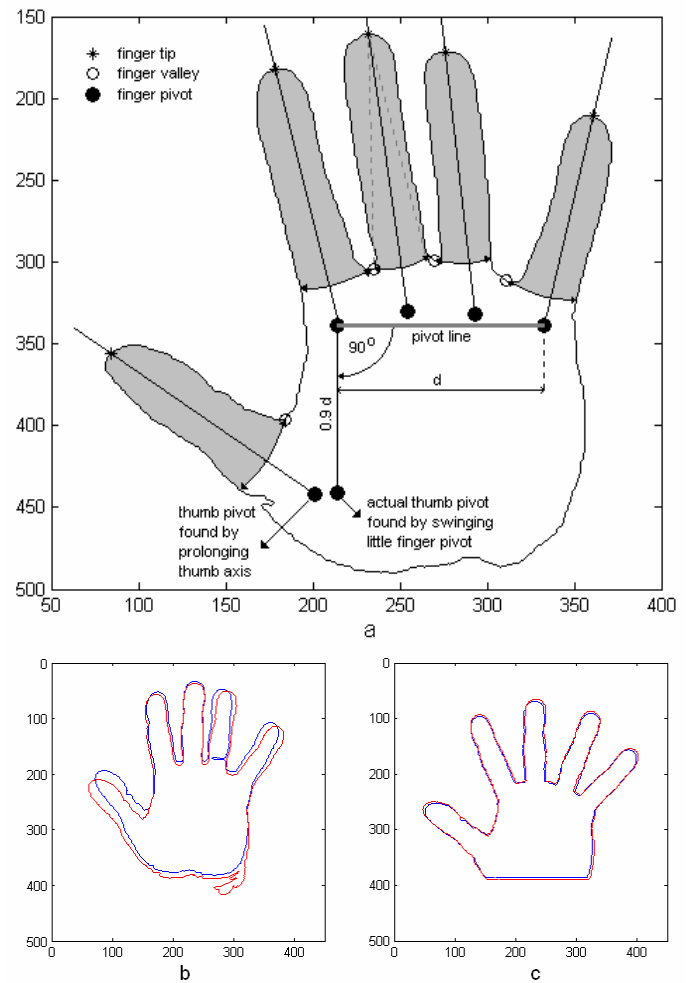

Figure 2: a) Fingers extracted by a sickle sweep, finger axes, finger pivots and definition of hand pivotal axis, Two superposed contours of the hand of the same individual; b) Before normalization, c) After normalization

little fingers (Fig. 2a). We call this line, the pivot line of the hand. The pivot line serves first, to register all hand images to a chosen pivot line angle (this angle was chosen as 80 degrees with respect to the x-axis), and secondly, as a reference for the rotation angles of the fingers. Thirdly, the orientation and size of the pivot line helps us to register the thumb and to establish the wrist region.

d) Rotation of the fingers: We calculate the major axis of each finger from its own inertial matrix. The actual orientation angle of the finger is deduced as $\theta = \arctan(v_{maj} / u_{maj})$, where $[u_{maj}\ v_{maj}]^T$ is the major eigenvector. Then each finger i is rotated by the angle $\Delta\theta_i = \theta_i - \psi_i$, for i = index, middle, ring, little, and where ψ_i is the goal orientation of that finger. The finger rotations are performed by multiplying the

Figure 3: ICA hand patterns; a) ICA1 hands, b) ICA2 hands.

Table I: The angles for the fingers of the proto-hand given in degrees.

Thumb	Index	Middle	Ring	Little
150	120	100	80	60

position vector of the finger pixels by the following rotation matrix around a pivot:

$$\mathbf{R} = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix}$$

The standard angles of the fingers are deduced from an average hand and are given in Table I.

e) Processing for the thumb: The motion of the thumb is somewhat more complicated as it involves rotations with respect to two different joints. In fact both the metacarpal-phalanx joint as well as the trapezium-metacarpal joint play a role in the thumb motion. We have compensated for this relatively more complicated displacement by a rotation followed by a translation.

A concomitant difficulty is the fact that the stretched skin between the thumb and the index finger confuses the valley determination and thumb extraction. For this purpose we rely on the basic hand anatomy, and the thumb is assumed to measure the same length as the person's little finger. The tip of the segment line from the thumb extremity to 120% extension below is found. To account for the more complicated thumb movement, the thumb is translated so that its pivot coincides with the tip of the pivot line, when the latter is swung 90 degrees clockwise, as illustrated in Fig. 2a. The thumb is finally rotated to its final orientation and merged back into the hand.

f) Centering and rotation of the hand: After normalizing finger orientations, hands are translated so that their centroid, defined as the mean of the four pivot points, is moved to a fixed reference point in the image plane. Finally the whole hand image is rotated so that its pivot line aligns with a fixed orientation. Alternatively, the hands could be registered with respect to their major inertial axis and centered with respect to the centroid of the hand contours (and not the pivotal centroid).

g) Wrist Completion: The hand contours we obtain after segmentation have irregularities in the wrist regions, which occur due to clothing occlusion or the difference in the angle of the forearm and the pressure exerted on the imaging device. These irregularities cause different wrist segments in every hand image taken which will later affect the recognition rate. The solution to this problem is to create a uniform wrist region consistent for every hand image and commensurate with its size.

We investigated various curve completion schemes, such as Euler spiral [7] and opted for the simpler and more robust solution of guillotining and smoothing the hand. In other words we connect the two sides of the palm by a straight line at the latitude of one pivot line length, parallel and below the pivot line.

4. FEATURE EXTRACTION AND RECOGNITION

There are several feature alternatives in order to discriminate between hands in a biometric application, from shape features to transform coefficients. Recently Independent Component Analysis (ICA) has proved to be a very viable feature extraction technique in image processing, with applications from face recognition to target discrimination [3, 1]. In our case, the scene is a binary image consisting of the silhouette of the normalized hand. However, the ICA analysis can easily be extended to appearance-based hand image, allowing us to include texture as well as palm print patterns.

Features from Independent Component Analysis: The Independent Component Analysis (ICA) is a technique for extracting statistically independent variables from a mixture of them. Generally, one assumes that each observed signal $\{x(k), k = 1,...,K\}$ is a mixture of a set of N unknown independent source signals $\{s(k), k = 1,...,K\}$, through an unknown mixing matrix $\mathbf{A}$. With x_i and s_i (i=1,…,N) forming the rows of the N×K matrices $\mathbf{X}$ and $\mathbf{S}$, respectively, we have the following model: $\mathbf{X} = \mathbf{AS}$. The data vectors, $\mathbf{X}$, for the ICA analysis are the lexicographically ordered hand image pixels. The dimension of these vectors is K (for example, K = 40,000, if we assume a 200×200 hand image). Briefly, ICA aims to find a linear transformation $\mathbf{W}$ for the inputs that minimizes the statistical dependence between the output components y_i, the latter being estimates of the hypothesized independent sources s_i: $\hat{\mathbf{S}} = \mathbf{Y} = \mathbf{WX}$.

In order to find such a transformation $\mathbf{W}$, which is also called separating or de-mixing matrix, we implemented the fastICA algorithm [5] that maximizes the statistical independence between the output components using maximization of their negentropy. There exist two possible formulations of ICA [1], depending on whether one wants the basis images or their mixing coefficients to be statistically independent. These two approaches depicted in Fig. 3, are called ICA1 and ICA2 architectures, respectively.

Table II: Correct recognition performances as a function of set size

	ICA1			ICA2		
Hand set size	20	50	91	20	50	91
Pc: single training set	96.89	94.85	93.77	97.92	97.33	96.89
Pc: double training set	97.92	96.00	94.87	98.54	98.81	98.53

5. EXPERIMENTAL RESULTS

The hand database we used contained 273 images of left hands of 91 different persons, each person having separately acquired three images of his left hand [2]. The images with size 1754×1276 pixels were acquired with a HP Scanjet 5300c scanner using a resolution of 150 dpi. There were no control pegs to orient the fingers, and there were no restrictions on hand accessories, like rings. Each person underwent three hand scan sessions at different times, and between the sessions the subject could add or remove, at will, rings, or roll up or down sleeves. Thus for each individual, three hand images were recorded, denoted by the sets A, B, C. First, the hand recognition experiments, based on normalized hand images, were performed on three selected population sizes, namely, population subsets consisting of 20, 50 and 91 individuals. Different population sizes help us perceive the recognition performance with increasing number of individuals. A boosting algorithm was applied so that several different formations of subsets (of sizes of 20 and 50) were created by random choice.

Secondly, we wanted to see the effect of training sample size, that is, the impact of multiple independent recordings of the individual's hand. Thus we ran the recognition experiments with a single training and then with the double training set, both in a round robin fashion. More explicitly, in the single set experiments, the ordering of the test and training sets were {(A,B), (B,A), (A,C), (C,A), (B,C), (C,B)}. In other words, set A hands were tested against the training set of set B etc. In the double training set, the ordering of the test and training sets were {(A, BC), (B, AC), (C, AB)}, e.g., hands in the test set A were recognized using hands both in the sets B and C. Finally the recognition scores given in Table II, were averaged from these training and test set combinations.

The results, shown in Table II, are very encouraging. It can be observed that accurate hand-shape based recognition is feasible with populations of up to one hundred.

6. CONCLUSION

We have shown that hand shape sensing can be a viable scheme for recognizing people with high accuracy, at least for population of sizes within hundreds. It constitutes an unobtrusive method of person recognition and it does not suffer from the confounding factors of accessories, illumination effects and expression as in the case of faces. Accurate person recognition depends critically upon deformable registration of the hand.

We pursue presently investigation of other shape features for hands, such as axial radial transform [9], Fisher hands or kernelized versions of principal component analysis or linear discriminant analysis. Normalization of hands based on active contours, provided reliable landmarks can be initially obtained, is another alternative. In this study only the left hands of people have taken a role. The improvement in the recognition rate with the use of the images of both hands or with a more extended set of training images, i.e., more than three images per person must be studied. Conversely, experiments should be carried out with hand set sizes going from hundreds toward thousands to determine the limitations in classification performance. Finally, the hand color and texture and/or the palm print [4], in addition to the hand shape could be judiciously combined to enhance recognition.

REFERENCES

[1] M. S. Bartlett, H. M. Lades, and T. J. Sejnowski, "Independent component representations for face recognition," in *Conference on Human Vision and Electronic Imaging III*, San Jose, California, 1998.

[2] S. Garcia-Salicetti, C. Beumier, G. Chollet, B. Dorizzi, J. L. les Jardins, J. Lunter, Y. Ni, and D. Petrovska-Delacretaz, "BIOMET: a multimodal person authentication database including face, voice, fingerprint, hand and signature modalities," in *International Conference on Audio- and Video-based Biometric Person Authentication*, 2003.

[3] B. A. Draper, K. Baek, M. S. Bartlett, and J. R. Beveridge, "Recognizing faces with PCA and ICA," *Computer Vision and Image Understanding* 91 (1-2), 115-137, 2003.

[4] C.C. Han, H. L. Cheng, C. L. Lin, and K. C. Fan, "Personal Authentication using Palm Print Features," *Pattern Recognition* 36(2003), 371-381.

[5] A. Hyvarinen and E. Oja, "Independent component analysis: Algorithms and applications," *Neural Networks* 13 (4-5), 411-430, 2000.

[6] A. K. Jain and S. Pankanti, "Biometric Systems: Anatomy of Performance," *IEICE Trans. Fundamentals*, Vol. E84-D, No. 7, pp. 788-799, July 2001.

[7] B. B. Kimia, I. Frankel, and A. M. Popescu, "Euler Spiral for Shape Completion," *International Journal of Computer Vision* 54(1/2), 157–180, 2003.

[8] Y. L. Lay, "Hand shape recognition," *Optics and Laser Technology*, 32(1), 1–5, Feb. 2000.

[9] E. Konukoğlu, E. Yörük, J. Darbon, B. Sankur, "Shape-Based Hand Recognition," submitted to *IEEE Image Processing*, 2003.

[10] R. Sanches-Reillo, C. Sanchez-Avila, and A. Gonzalez-Marcos, "Biometric Identification through Hand Geometry Measurements," *IEEE Transactions of Pattern Analysis and Machine Intelligence*, Vol. 22, No. 10, October 2000.

[11] W. Shu, G. Rong, and Z. Bian. "Automatic palm print verification," *International Journal of Image and Graphics*, 1(1):135–151, 2001.