THE BIOSECURE GEOMETRY-BASED SYSTEM FOR HAND MODALITY

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ABSTRACT

We present an identification and authentication system based on hand modality which is part of a reference system for all modalities developed within the Biosecure consortium. It relies on simple geometric features extracted from hand boundary. The different steps of this system are detailed, namely: pre-processing, feature extraction and hand matching. This system has been tested on the Biosecure hand database which consists of 4500 hand images of 750 individuals. Results are detailed with respect to different enrolment conditions such as population size, enrolment size, and image resolution.

Index Terms— hand modality, biometry, reference systems, hand database, geometry-based features

1. INTRODUCTION

Accessing secured places or devices require secured systems that can identify and/or authenticate authorized users and reject the others. For this purpose biometrics systems have been developed which rely on human physical characteristics. Biometric systems are based on various modalities such as hand, iris, fingerprints, voice or face [1]. The hand modality has a number of advantages in that it is user-friendly, hand-imaging devices are not intrusive, and template storage costs are small. Several systems have been developed using the hand modality. They are based on the hand silhouette [1, 2, 3, 4], hand geometry [5, 6, 7, 8, 9, 10], finger biometry [11, 12] or palmprints [13, 8]. We present here a geometry-based system that has been developed within the Biosecure Network of Excellence [14, 15]. The network has been promoting since 2004 the development of biometric reference systems and reference databases. Reference systems are intended to be open-source softwares and databases are intended to be available publicly. The geometry-based reference system for the hand modality is part of a larger system for both geometry-based and appearance-based features [3].

The reminder of this paper is as follows. First we describe the geometric-based identification and authentication system in section 2. Then we present some results on the Biosecure database. We emphasize the effect of different enrolment conditions (i.e., image resolution, enrolment size and population size) on the system performances.

2. GEOMETRY-BASED SYSTEM

Our system relies on some finger geometry measurements. It is assumed that fingers are not in contact with each other and that the hand is lying flat. However, the hands can be in arbitrary postures and orientations. No control pegs are used. The hands can wear accessories such as rings and bracelets or the sleeve can occlude partly the palm.

The image is first binarized. The presence of rings may result in disconnected fingers which are reconnected by a robust approach based on generalized connectivity. The finger valley points are then searched from boundary points. Then, for each finger we find its major axis and compute the histogram of the Euclidian distances of boundary points to this axis. The five histograms are normalized and are thus equivalent to probability density functions. These five densities constitute the features of the hand boundary. Then, given a test hand and one of the enrolled hands, the symmetric Kullback-Leibler distance between the two probability densities is computed separately for each finger. The distances are summed yielding a global matching distance between the two hands. Fig 1 presents the block diagram of the system.

2.1. Hand shape extraction

The hand shape extraction module segments the hand from the background and reconnect fingers which may have been disconnected because of the presence of rings.

We first threshold the original image (see Fig 2a and Fig 2b). After binarization, the hand major axis, which corresponds to the hand orientation, is computed through the eigenvectors of the inertia matrix. We define the latitudinal axis as a line orthogonal to the major axis at the point where palm width is maximal. Latitudinal axis divides the hand in two parts (wrist or fingers) depending of hand direction. This process is depicted on Fig 2c. A line, orthogonal to hand major axis and crossing the fingers, presents alternate segments

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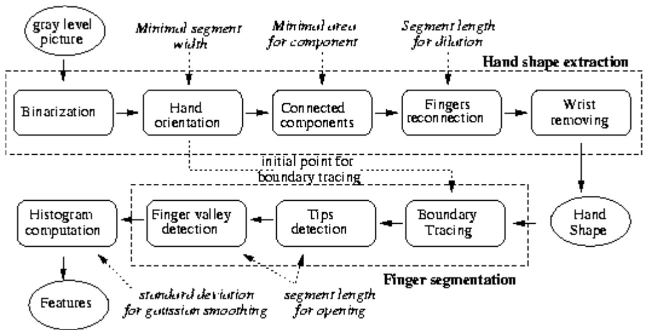

Fig. 1. Block diagram of the processing steps for extracting the geometry-based hand features. Boxes represent algorithmic steps, ellipses represent data and dashed lines represent parameter inputs.

of background/object color. This allows us to identify hand direction.

Due to the presence of rings, some fingers may be isolated and disconnected after hand thresholding. These isolated fingers are detected by searching for large enough connected components (the minimal component area is deduced from image size). The biggest component is the hand; the others correspond to potential disconnected fingers. We reconnect the selected components using a morphological dilation. The structural element is a linear segment parallel to the component major axis and in the direction of the palm. If dilation does not reconnect this component with the palm, it is eliminated. The length of the structural element depends on image height. Next, the wrist line (see Fig. 2c) is established: starting from the latitudinal axis whose associated segment is of length L (largest palm width), we consider the closest parallel line whose segment length is less than $\frac{1}{2}L$ and we remove all points below it.

2.2. Feature extraction

The contour of the hand shape is extracted through a boundary-selection algorithm. The starting point is chosen at the intersection of the hand major axis and the wrist line. Then the radial distance curve is computed with respect to this initial point. The radial distance is the Euclidian distance between each boundary point and the initial point [3]. The positions of the finger tips are found from the radial distance curve by searching for their extrema. To avoid spurious local maxima, the curve is first smoothed through a morphological opening. The structural element is a centered linear segment whose size is adaptively chosen so that only five extrema are found (one for each finger). The same analysis is done on the inverted radial distance curve in order to find the four finger valley points. The result of this process is depicted in Fig. 2d.

This approach allows us to find finger valley points which are placed on local maxima of the radial curve only. The positions of the three remaining exterior valley points have still to be estimated (at the left of the thumb, at the left of the index and at the right of the little finger). For each finger, the tips and at least one valley point is known. The Euclidian distance between those points is projected on the finger boundary to find the remaining point on the boundary. Once all finger valleys are found, we can easily segment fingers from hand and compute each finger's major axis. The final result is shown on Fig. 2e.

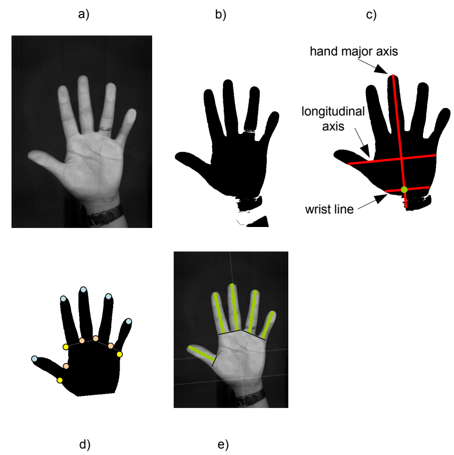

Fig. 2. Processing steps and feature extraction for the identification and authentication geometry-based system. a) Original image. b) Binarized hand with one finger disconnected. c) Hand component with reconnected finger, construction lines (hand major axis, centerline and wrist line) and contour starting point at the intersection of the wrist line and the hand major axis. d) Hand with removed wrist region, the five tip points, the four valley points extracted from the radial distance curve, and the two estimated valley points. e) Segmented fingers and finger major axes.

For each finger, we project each boundary point on the finger major axis. The lengths of the projected segments are computed and we get a histogram of these lengths. The histogram is restricted to 100 quantified values and then normalized by the number of points yielding a probability distribution of the lengths. Next we smooth this distribution with a Gaussian operator. (we set the standard deviation to 0.2). Thus the feature set consists of 5x100 features including 5 distributions.

2.3. Hand Matching

The hand matching between an enrolled hand and a test hand, relies on a global distance resulting from the comparison of the five finger distributions. We use the symmetric Kullback-Leibler distance [16] to compare the histogram distribution of two fingers (the tested one, and the reference one). First separate five finger-to-finger distances are computed. The global distance results from the summation of the three lower distance scores are considered. In this sense, we consider the one-sided trimmed mean of finger distances. Finally, for identification and verification tasks, the minimal distance between the test hand and the enrolled hand(s) is declared as the owner of the test hand. Two hands of the same owner are considered independent, i.e. there is no fusion score.

3. EXPERIMENTS

The Biosecure database consists of 4700 hand images from 750 individuals. For a subset of 642 individuals, there are ambidextrous recordings (left and right hands). For another subset of 114 individuals, there are different resolution images recorded (150, 400 and 600 dpi). There are 3 hands registered for each individual but for a subset of 78 individuals, there are 6 recordings, including time lapse data. The Biosecure database allows thus to test different scenarii, by varying enrolment conditions. In the following, we test the system under variables such as population size, enrolment size and image resolution. The recognition system addresses the two related tasks of verification and identification. Verification means that the system must decide whether a test hand corresponds to the claimed identity within enrolled hands. The verification performance (VP) is documented in tabular form via $VP = 1 - EER$ (Equal Error Rate) as well as via Receiver Operating Characteristic (ROC) curves. Identification means that the identity of an unknown test hand is to be recognized within the enrolled hand set. The identification performance (IP) is documented in tabular form True Positive rate, that is, the percentage of correctly identified test cases as well as via CMC (Cumulative Match Count) curves.

3.1. Global performance on the Biosecure database

The geometry-based system is tested on the left and right hand sets of the Biosecure database (750 individuals). For each individual, there are 3 registered hands and two of these hands are used as enrolled hands. The results are given by averaging the rates of a three-fold experiments. The verification performance rate (VP) and identification performance rate (IP) are given in Table 1 (a) while the ROC and CMC curves are depicted in fig 3.

3.2. Performance wrt enrolment, population size and resolution

We first evaluate the effect of enrolment (En: number of enrolled hands per individual) on system performance. For that purpose, we test the left hand set of the Biosecure database. As three hands are registered per individual, one of them is used for testing and the other two for training (En = 2) or two of them used for testing and one for training (En = 1). The verification and identification performance rates are given in Table 1 (a). Enrolling 2 hands rather than one hand always yields better performances in identification or verification. This yields higher system costs as the features corresponding to two hands rather than one are stored in memory, and twice comparisons are made.

Then we test the effect of increasing population (number of individuals registered) on system performance. For each population size, eight sets are randomly built and the results averaged. The performance scores are given in Table 1. There are two enrolled hands per individual. System performances are robust to the increase of population for the verification task.

To test the effect of image resolution, the original 150 dpi original images are down-sampled to lower resolutions. Performances do not vary between 90 and 150 dpi. Table 1 shows the results with six different resolutions. For the verification task, low-resolution images (as low as 30 dpi) are still efficient. The identification task benefits from higher resolutions: maximum is obtained between 90dpi and 120dpi.

Table 1. Verification (VP) and Identification (IP) performances on the Biosecure database. (a) Performance on left and right hand sets with a population of 750 users, a resolution of 150dpi and 2 pictures for enrolment. Table (b) (c) and (d) show parameters effects (left hand set) (a) enrolment size, (c) population size and (d) image resolution.

(a) Global Performance		
	Left hands	Right hands
VP	95.81	95.49
IP	88.95	85.85

(b) Enrolment size		
	1	2
VP	92.43	94.83
IP	75.83	87.32

(c) Population size					
	100	200	450	600	750
VP	95.74	95.76	95.75	95.80	95.79
IP	93.54	91.92	89.94	89.42	88.92

(d) Image resolution						
	30dpi	45dpi	60dpi	90dpi	120dpi	150dpi
VP	94.31	94.89	95.11	95.73	95.46	95.81
IP	77.81	85.47	87.23	89.26	89.26	88.95

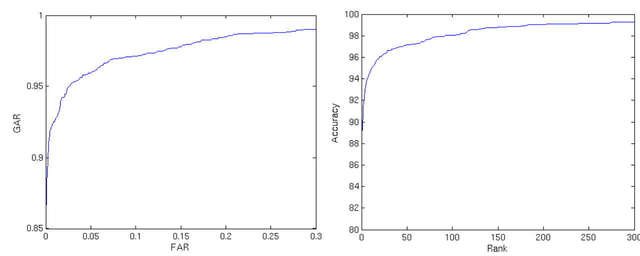

Fig. 3. ROC curve (left) and CMC curve (right) for the Biosecure database (Enrolment 2, Population 750, Left hand set)

Table 2. Performance wrt high resolution, compared to 150 dpi. 150-600dpi correspond to 600 dpi images downsize to 150dpi.

	150 dpi	400 dpi	600 dpi	150-600 dpi
VP	99.42	99.12	98.09	98.83
IP	99.42	98.83	89.18	98.25

3.3. High Resolution images

We also perform tests with the set of high resolution images registered at higher resolutions (400 dpi and 600 dpi) for 114 individuals. The feature vector has to be enlarged to 500 values per finger so that the total amount of features is 2500 values. Contrary to former tests, image are not down-sampled: 3 images per resolution are available for each individual. Two of them are used for enrolment. Table 2 shows identification and verification performance at the different resolutions.

We observe that results decrease significantly when resolution increases. We have checked that the segmentation is not robust: the hand boundary is less stable for high resolution images compared to low resolution images. Indeed, this behavior is mainly due the fact that high resolution images present ramps and shades along finger boundaries. The latter is not observed with low resolution images and thus a simple thresholding yield good result. However, for high resolution images, the segmentation may yield oscillatory and non robust boundaries. Note that thresholding is the main process for segmentation for common hand based biometric systems [3, 4, 12] and thus would also fail for high resolution images.

4. CONCLUSION

We have described a hand biometric system which relies on geometry-based features. We have then studied the influence of various parameters such as enrolment size, population size and image resolution, on the performances of this system. The system has been tested on the Biosecure hand database which will soon be publicly available and which includes 4500 hand images with various hand postures and artifacts. Similarly, the source codes for the whole reference system (geometry-based and appearance-based systems) is available at `https://trac.lrde.org/hands`. Further work consists in exploiting and testing the system under other conditions such as multi-hand scheme and time lapse. A comparison with another geometrical based system must be done [5]. We also work on a new segmentation scheme for high resolution images. A robust segmentation scheme is currently under investigation.

5. REFERENCES

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