Comparison of Distance-Based Features for Hand Geometry Authentication

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Abstract. A hand-geometry recognition system is presented. The development and evaluation of the system includes feature selection experiments using an existing publicly available hand database (50 users, 500 right hand images). The obtained results show that using a very small feature vector high recognition rates can be achieved. Additionally, various experimental findings related to feature selection are obtained. For example, we show that the least discriminative features are related to the palm geometry and thumb shape. A comparison between the proposed system and a reference one is finally given, showing the remarkable performance obtained in the present development when considering the best feature combination.

Keywords: Hand geometry, biometrics, feature selection.

1 Introduction

Nowadays, people identification to control access to certain services or facilities is a very important task. The traditional method to assert that a person is authorized to perform an action (e.g. using a credit card) was the use of a password. This kind of identification methods has the problem of usually requiring long and complicated passwords to augment the security level, at the cost of user inconvenience.

People identification through biometric traits is a possible solution to enable secure identification in a user convenient way [1]. In biometric systems, users are automatically recognized by their physiological or behavioral characteristics (e.g. fingerprint, iris, face, hand, signature, etc.) In the present work, we focus on hand biometrics. Traditional hand recognition systems can be split in three modalities: geometry, texture and hybrid. We concentrate our efforts in the first one due to its simplicity.

In the literature, several hand geometry recognition systems have been developed [2-4]. For example, in [2] a hand recognition system is presented based on various fingers widths, heights, deviations and angles. The work described in [3] treats the

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fingers individually by rotating and separating them from the hand. Oden *et al.* [4] used the finger shapes represented with fourth degree implicit polynomials.

On the other hand, in [5] only palm texture information of the hand is used to identify a user. Finally, a third kind of hand recognition methods employ fusion of hand geometry and texture, as for example [6].

As mentioned before, the present work is focused on hand geometry. In particular, we implement and study a distance-based hand verification system based on hand geometry features inspired by previous works [2,8]. These features are compared in order to find new insights into their discriminative capabilities. As a result, we obtain a series of experimental findings such as the instability of features related to the thumb shape and location. A comparison between the proposed system and a reference one is finally given, showing the remarkable performance obtained in the present development when considering the best feature combination.

The rest of the paper is structured as follows. In section 2 we describe the processing blocks of our authentication system based on hand geometry. Section 3 describes the experimental results and observations obtained related to feature selection. Finally, conclusions are drawn in section 5, together with the future work.

2 Distance-Based Hand Geometry Authentication

The global architecture of our system is shown in Fig. 1. The first step is a hand boundary extraction module, from which the hand silhouette is obtained. The radial distance from a fixed reference point is then computed for the silhouette to find, for all fingers, their valleys and tips coordinates. Then, some distance-based measures considering these reference points are calculated to conform the feature vector representation of the hands. Given test and enrolled hands, the matching is based on a distance measure between their feature vectors.

2.1 Boundary Extraction

Input images are first converted to a gray scale and then binarized using Otsu's method. A morphological closing with a small circle used as structuring element removes spurious irregularities. After that, we search for the connected components present in the image assuming that the largest component is the hand and the others (if any) are potentially disconnected fingers or noise. Various shape measures are computed for the disconnected components found in order to detect disconnected fingers (e.g. due to rings), case in which we reconnect the finger to the hand using morphological operations.

Once the hand boundary is extracted, we detect the wrist region. To do so, we search for the segment perpendicular to the major axis of the hand, closest to the center of the palm with a length equal or less than half of the maximum palm width (see Fig. 1 for example images).

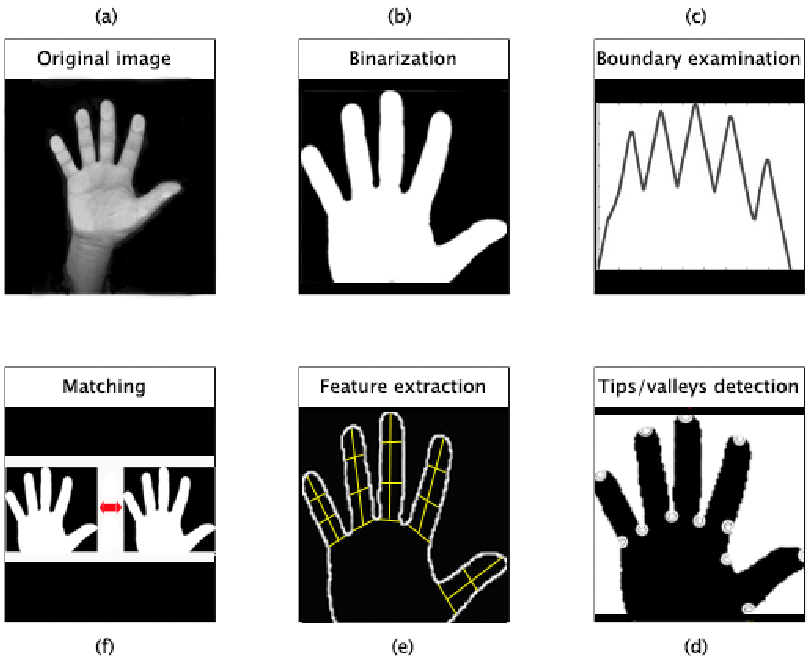


Fig. 1. Block diagram of the main steps followed in our system to extract features and matching two hands. Original image (a) is first binarized (b). The boundary is then calculated and the plot (c) of the radial distance from a reference point lets us estimate the coordinates of tips and valleys (d). After that, feature extraction is done by measuring some finger lengths and widths (e). Last, given two hands, their matching is based on a distance between their feature sets.

2.2 Tips and Valleys Detection

Once the boundary of the hand is available we fix a reference point in the wrist, from which the boundary is clockwise scanned calculating the Euclidean distance to the reference point. The resulting one-dimensional function is examined to find local maxima and minima. Maxima of the curve correspond to finger tips and minima are associated to finger valleys. Depending on the hand acquisition, first maxima will correspond to the thumb or to the little finger. This process is depicted in Fig. 1c.

Before feature extraction, we compute a valley point for every finger at each side of its base (left and right). The only two fingers for which a simple analysis of the previous minima results in these valley points are the middle and ring fingers. For the other fingers we take as reference point the only available valley associated to the finger, and then we compute the Euclidean distance between this point and the boundary points at the other side of the finger. The point that yields the minimum distance is selected as the remaining valley point for that finger.

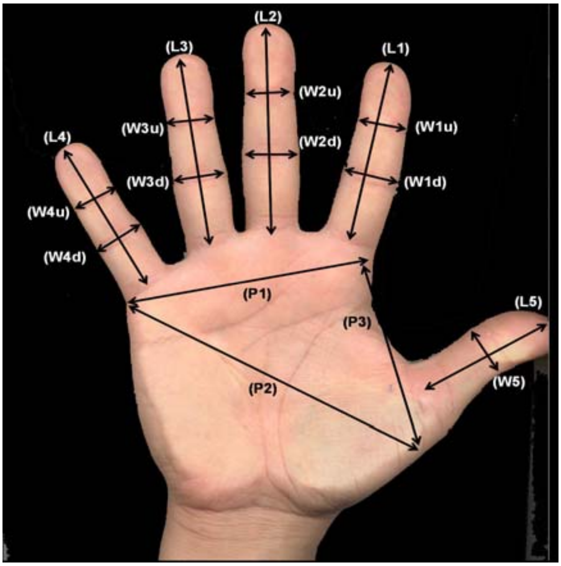


Fig. 2. Set of features studied in the proposed hand geometry authentication system

2.3 Feature Extraction

We define the reference point of a finger as the middle point between the two finger valleys. The length of the finger is calculated as the Euclidean distance from the tip to the finger reference point. Fig. 2 shows the notation used to name the hand features we propose. For each finger, its length is denoted with letter 'L' and a number that identifies the finger (1 for index, 2 for middle, 3 for ring, 4 for little and 5 for thumb). Finger widths ('W') keep the same numbering with an additional character indicating if it is the upper ('u') or the lower width ('d'). See Fig. 3. The thumb only contains one width measure, at the middle of the finger, denoted as W5. There are also some palm distance features named as P1, P2 and P3 (see Fig. 2).

In the experimental section we will study various combinations of these features.

2.4 Similarity Computation

Once the feature vector has been generated, the next step is to compute the matching score between two hands. In our system, based in a distance measure, lower values of the matching score represent hands with higher similarity, therefore the matching score represents dissimilarity.

If we denote the feature vector of one hand as $m_1[i]$, $i = 1,\ldots,N$, and the feature vector of another hand as $m_2[i]$, $i = 1,\ldots,N$, then their dissimilarity is computed as:

$$d(m_1, m_2) = \sum_{i=1}^{N} \left| m_1[i] - m_2[i] \right| \tag{1}$$

with N being the length of the feature vectors.

3 Experiments

In the first section, the database used in this work is detailed and the protocol used to generate genuine and impostor scores is explained. The reference system is summarized in section 3.2. Finally, the results obtained in the feature selection experiments are shown. The best combination achieved will be included in the final system to evaluate its performance in comparison to the reference system.

3.1 Database and Experimental Protocol

The experiments have been carried out using a publicly available database, captured by the GPDS group of the Univ. de Las Palmas de Gran Canaria in Spain [8]. This database contains 50 users with 10 right hand samples per user. The image acquisition was supervised: users cannot place the hand in the scanner in any position, scanner surface was clean, illumination was non variable, etc. Hence, high quality images were obtained.

To fairly compare the performance of our system with the reference one, both systems were tested over the same database using the same protocol. Impostor scores are obtained by comparing the user model to one hand sample (the sixth one) of all the remaining users. Genuine scores are computed by comparing the last 5 available samples per user with its own model (which is constructed with the first hand sample). This protocol uses one sample per user for enrollment and five samples per user for test. Overall system performances are reported by means of DET plots [10].

3.2 Reference System

Fig. 3 shows the processing steps of the recognition system used as reference for comparison with our development. This reference system is fully described and available through [9]. In the reference system the image is first preprocessed and then,

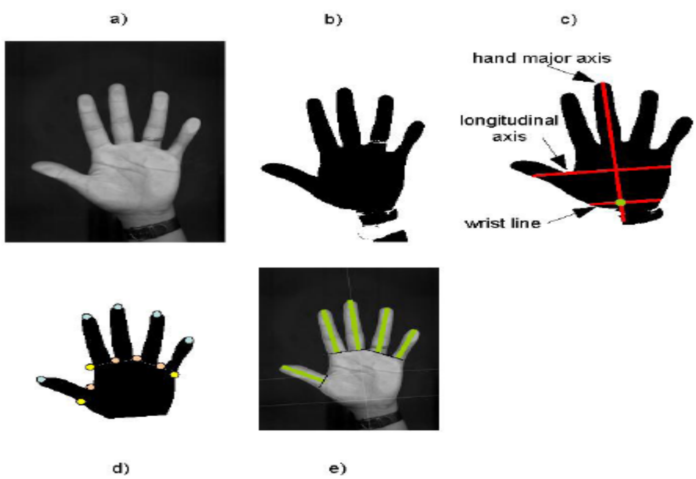


Fig. 3. Processing steps and feature extraction for the reference system (extracted from [7])

for each finger, the histogram of the Euclidean distances of boundary points to the major axis of the finger is computed. The features of the hand boundary are the five normalized histograms.

Then, given two hands, the symmetric Kullback-Leibler distance between finger probability densities is calculated in order to measure the grade of similarity.

3.3 Experiments

The set of features presented in Sect. 2.3 consists of 17 measures from different zones of the hand. Specifically, there are five finger lengths, nine finger widths and three palm widths. This set of features is based on a selection from the best features proposed in [8] and some features studied in [2].

In our first experiment, some subsets of features were manually chosen and then tested to check their performance. Table 1 shows the results. We observe that not considering the information of the thumb in the feature set (feature subset 2 vs. feature subset 1) provides a significant performance improvement (from more than 9.6% to less than 1.7% EER). This is in accordance with the results presented in [4], and may be due to the freedom of movement of this finger, which makes hard to estimate correctly its valley points. Because of this, for the rest of experiments we discard the features related to the thumb (i.e., L5 and W5).

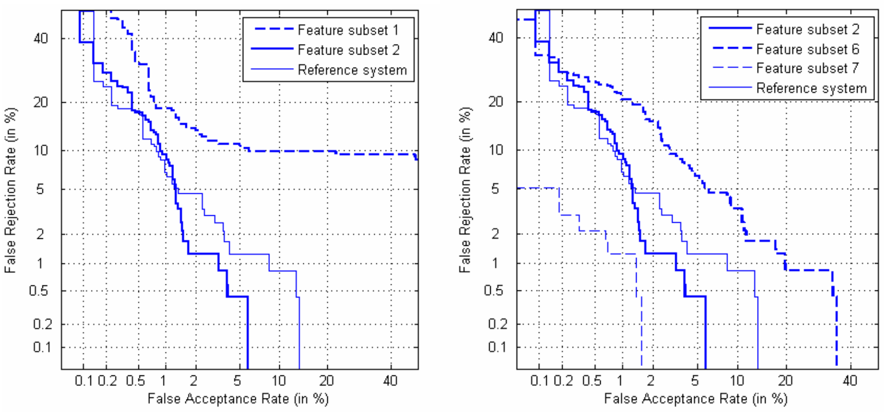
Also interesting, the lengths of the four remaining fingers are useful because removing any of them deteriorates the system performance (subsets 3, 4 and 5 vs. subset 2).

On the other hand, the palm lengths considered (P1 to P3) do not provide any benefit (subset 6 vs. subset 2). Maybe, this is due to the fact that these features related to the palm use the three exterior valley points which are most difficult to be precisely estimated. Finally, in Table 1, we can see that the basic information provided by the finger lengths (subset 2) benefits from the incorporation of the finger widths (subset 7).

The system performance for the feature sets present in Table 1 is analyzed for all the verification threshold operating points by means of DET plots in Fig. 4. Fig. 4a shows the DET plot of: (i) the five finger lengths (feature subset 1), (ii) four finger lengths, excluding the thumb (feature subset 2) and (iii) the reference system.

Table 1. EER for different subsets of features. Feature nomenclature is the same as the one used in Fig. 2.

Feature subset ID	Features	Equal Error Rate (%)
1	L1, L2, L3, L4, L5	9.66
2	L1, L2, L3, L4	1.68
3	L1, L4	5.70
4	L2, L3	4.83
5	L2, L3, L4	3.06
6	L1, L2, L3, L4, P1, P2, P3	5.54
7	**L1, L2, L3, L4, W1u, W1d, W2u, W2d, W3u, W3d, W4u, W4d**	**1.24**
8	L1, L2, L3, L4, W1u, W1d, W2u, W 2d, W3u, W3d, W4u, W4d, P1, P2, P3	5.09
Reference system		2.97



(a) (b)

Fig. 4. (a) Performance obtained using three different feature sets. This experiment reports results about which fingers must be included in the feature set. (b) DET comparative between four proposed feature sets. In this picture, the influence of palm and finger widths is examined.

Fig. 4b shows the results of the system evaluation with: (i) four finger lengths, excluding the thumb (feature subset 2), (ii) the set used in (i) plus palm widths (P1 to P3) (feature subset 6), (iii) four finger lengths and their associated widths (feature subset 7) and (iv) the reference system.

Also interesting, the best Equal Error Rate achieved in the proposed system (1.24%) is lower than the reference system (2.97%).

4 Conclusions and Future Work

A new recognition system based on hand geometry has been proposed. In this work, different sets of features have been evaluated and some experimental findings have been obtained. We have observed that the features based on the thumb are the least discriminative. This may be due to its freedom of movement, which makes hard to estimate correctly the valley points that define this finger.

For the four remaining fingers, we have concluded that their lengths and widths are the most discriminative features. Also interesting, the palm widths report bad results, perhaps due to their relation with the thumb valley points. Finally, the results obtained for the best feature combination (1.24% EER) improve the reference system performance (2.59% EER) over the same database and experimental protocol with a relative improvement of more than 50% in the EER.

Future work includes applying feature subset selection methods to the proposed set of features and the development of quality detection algorithms to automatically discard low quality images which worsen the system performance.

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