Hand Geometry-based Biometric Systems

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Abstract. Hand geometry is a biometric that can be used in identification, but is more frequently used in identity verification. Measurements, e.g. finger widths and lengths, taken from a hand image can be stored in a database, and then compared with measurements taken from a new image. Typical applications are in access control. In verification systems the new image is compared against one template in the database to verify or deny a claimed identity. In identification all database entries are compared with the new image to choose the best match.

1 Introduction

Biometric systems are used in personal identification, i.e. associating an identity with an individual. The problem of resolving the identity of a person can be categorized into two fundamentally different types of problems, identification and verification. Identification answers the question "Who is this person?" while verification confirms or denies a person's claimed identity ("Is this person who he claims to be?") [1].

Hand geometry is a widely used sign of identity, i.e. a person can be identified by measurements of his or her hand. It does not achieve quite the same accuracy as some other methods, for example fingerprint or iris recognition, but has many advantages. Hand geometry systems are medium cost, as only a platform and a camera are needed, and the computation and storage costs are low, as hand measurement templates typically require only 9-25 bytes of memory each [2]. User acceptance is much higher than in many other systems, at it is less invasive to present your hand to the camera than your eye, for example. Hand geometry also lacks the negative association to criminal records, which causes some users to reject fingerprint recognition. These performance and acceptability issues are important considerations when designing a biometric system. Also circumvention, i.e. possibilities of fooling the system must be considered [3].

The architecture of a typical hand geometry system resembles the architecture of any other biometric system, consisting of an enrollment phase and a comparison phase [2]. In the enrollment phase photographs are taken and processed to extract the user's significant features and store them in a database. In the comparison or verification phase the features of the new photograph are compared with the templates in the database. In an identification system the matching is done against all templates in the database, and in a verification system the user provides an identity by presenting for example a code or an ID card, and only the corresponding template is compared to verify or deny the claimed identity.

This review presents some published approaches of extracting hand geometry features in section 2. In section 3 methods of comparing and classifying the features are discussed. Section 4 presents some commercially used hand geometry applications, and section 5 contains some conclusions.

2 Feature Extraction

2.1 Image Capturing and Preprocessing

The imaging equipment needed in a hand geometry identification or verification system is quite simple. Most systems include a platform, where the hand should be placed, and a camera.

The hand image for the system presented in [2] is captured by a CCD color camera placed above a platform designed to guide the hand to a fixed location. The platform has six tops in specific locations to guide the placement of the fingers. The tops are also equipped with pressure sensors, which trigger the camera when they are activated. In addition to the view of the back of the palm, the image contains a lateral view of the hand due to a mirror placed beside the platform. A very similar setup used by Jain et al [1], can be seen in figure 1. The setups basically differ only in that the mirror is placed on different sides of the hand, and that there is one guiding peg more in the system by Sanchez-Reillo et al [2].

In camera setups lighting conditions must be taken into consideration so that shadows do not change the hand profile. For example backlighting can be used, as in [4] (see figure 2 a). Instead of a camera setup, a scanner can be used. For example in [5] images were acquired with a regular document scanner.

The image must usually be preprocessed to make it easier to extract the features. In [2] the color image is transformed to a gray-scale image with the background eliminated. Deviations of the hand position within the image are corrected by resizing and rotation, and then a Sobel edge detection algorithm is performed to extract the contour of the hand. Typically just the contour image (see figure 2 b) or a binary image of the hand is used. Hand geometry, as the name says, concentrates on geometric features and does not utilize for example colors or intensities.

In recent applications published by Kumar et al [6] and Oden et al [4], the image capturing is made even more user friendly, as there are no pegs on the platforms. The users are only required to place their palm on the imaging table, without their fingers touching eachother. In [6] the captured image is binarized using a threshold operation, and aligned using rotation of a best-fitting ellipse (for explanation on best-fitting ellipse, see e.g. [7]). The estimated orientation of the binarized image is used to rotate the gray-level hand image, from which a palmprint image is extracted using morphological erosion. Palmprint features are used in addition to geometric measurements to identify a hand.

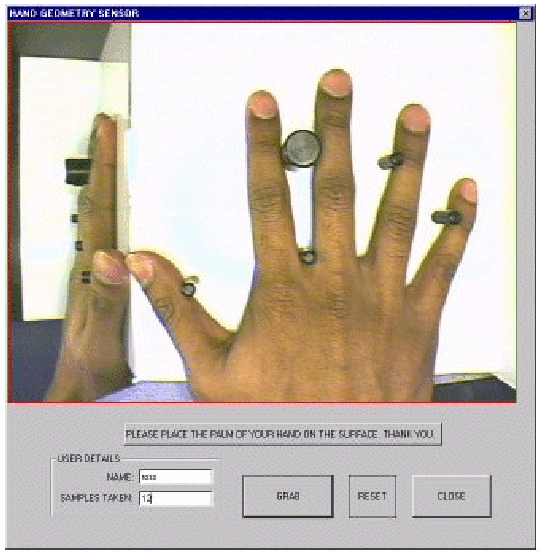
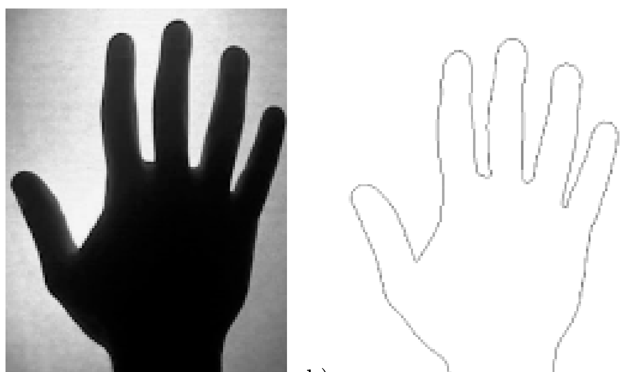


Fig. 1. Imaging setup for hand geometry application [1]



a) b)

Fig. 2. a) Hand image captured with backlighting, b) boundary image [4].

Images are captured the same way both in the enrollment phase and in the verification phase. A few or several images are typically taken of one user in the enrollment phase, and the average feature vector is stored as the template. In some systems the verification phase also includes some aspects of enrollment, i.e. the template vector can be recomputed to be an even closer match with the new image [1]. This helps keep the template up to date with the changes in the user's hand caused for example by aging, weight gain or weight loss.

2.2 Measurements and Feature Selection

Commonly measured features in hand geometry systems are finger lengths and widhts, and palm dimensions. Figure 3 shows a typical example, i.e. the measurements used in [1]. Also best fitting circles and ellipses can be used. For example in [5] features include the radius of the largest circle that fits onto the palm, as well as on two locations on each finger (see figure 4).

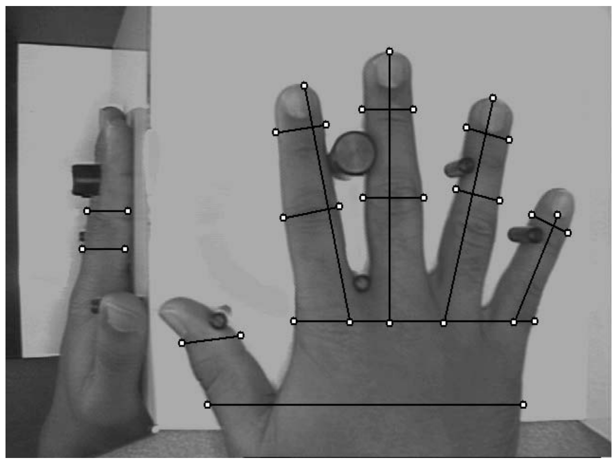


Fig. 3. Example of hand geometry features from [1]

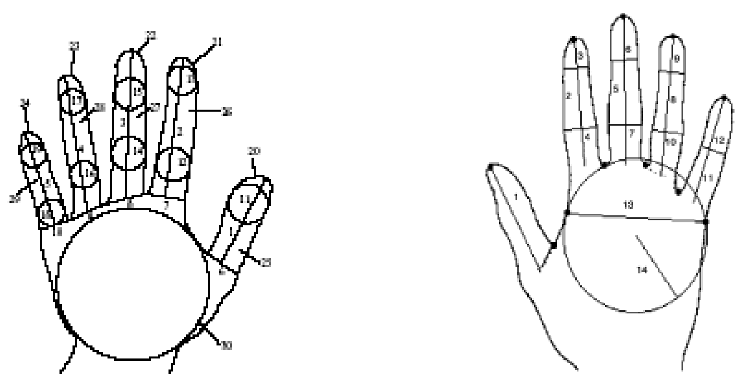


Fig. 4. More examples of hand geometry features from [5] (left) and [4] (right)

The system presented in [2] measures 31 hand features in total, including widths of 4 fingers at 4 different locations, the width of the palm, and the distances between the three interfinger points measured from the direct view, and finger heights and deviations measured from the side view. All measurements are taken relative to a determined measure to avoid variation caused by the user's weight gain or loss. In [8] the normalization is done by the first width measured of the middle finger.

Once the features are measured from several photographs of each user's hand, a statistical analysis can be performed to determine which features are the most useful in identification. The higher the ratio between the intraclass (images from one user) and interclass variability is, the more discriminant is the feature [2]. The variability ratio F_j of feature j is computed using standard deviations of the feature:

$$F_j = \frac{\text{interclass variability}}{\text{intraclass variability}} = \frac{\left(V \frac{1}{N} \sum_{i=1}^{N} \overline{f_j^i}\right)}{\frac{1}{N} \sum_{i=1}^{N} V\left(f_j^i\right)} \tag{1}$$

where V is the standard deviation function, N is the number of classes (users), f_j^i is the jth feature of the ith class, and $\overline{f_j^i}$ is the mean of the jth features of the ith class. In the example case described in the article, the number of significant features is reduced from 31 to 25 after the analysis, i.e. 6 features are not significant enough to be useful in recognition.

The application presented in [6] uses similar, but fewer, measurements, i.e. finger and palm widths and lengths. Lines and creases in the palmprint image are utilized to create a bimodal biometric system. This bimodality is unusually practical, as both biometrics can be measured from one image. Hand geometry is also ideally suited for integration with fingerprint recognition, for example by using hand geometry for frequent verification and then adding fingerprint biometrics for infrequent identification [1].

The shape distance computed during alignment of the hand image is the basis for the deformable matching hand verification system presented in [9]. The algorithm includes filtering out the finger alignment pegs, and extracting the contour of the hand. The actual matching is done by computing the distance between pairs of fingers, i.e. a finger in the new image and the corresponding finger in the database image. The Mean Alignment Error is examined in the verification phase to decide whether the pair of handshapes are from the same individual. An example of shape alignment can be seen in figure 5.

The recent application by Oden et al. [4] uses implicit polynomials to model the fingers, as seen in figure 6. From a single 2D view taken without guiding pegs (figure 2 a) a boundary image (2 b) is processed. Fingertips and interfinger points are found from the boundary using signature analysis. A moving average filter can be used on the 1D signal representing the boundary - local minima are interfinger points, and local maxima are finger tips. Using these points and simple analytic geometry rules, the needed handfeatures can be calculated, and fitted to an implicit polynomial model defined by:

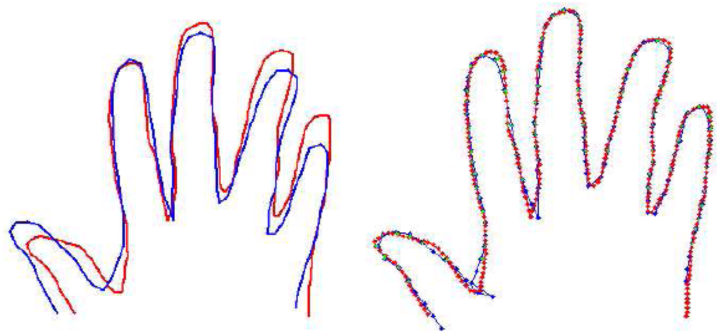


Fig. 5. Two hand scans from the same hand, overlaid (left) and aligned (right) [9]

$$f_n(x,y) = \sum_{0 \le i,j; i+j \le n} a_{ij} x^i y^j \tag{2}$$
$$= a_{00} + a_{10}x + a_{01}y + ... + a_{n0}x^n + a_{n-1,1}x^{n-1}y + ... + a_{0n}y^n = 0$$

The fundamental problem in implicit polynomials is the fitting, i.e. finding the polynomial coefficients that best represent the object. The fitting algorithm must be robust, i.e. small changes in data can not cause huge changes in the coefficients. Fitting algorithms include 3L-, gradient-one- and Fourier-fitting [4]. The coefficients represent features, and can be used in classifying the hand shape.

Fig. 6. Contour of finger and fitted 4th degree implicit polynomial from [4]

3 Classification and Verification

Extracted features can be compared using common distance measures, like Euclidean or Hamming distance. The Euclidean distance is defined as:

$$d = \sqrt{\sum_{i=1}^{L} (x_i - t_i)^2}, \tag{3}$$

where L is the dimension of the feature vectors, x_i is the ith component of the sample feature vector, and t_i the ith component of the template feature vector. The template feature vector is the mean of the feature vectors extracted from the photographs taken in the enrollment phase [2].

The Hamming distance measures the number of differing features. Obviously there is some variance even in feature components taken from the same user, but by the assumption that the feature components follow a Gaussian distribution, a limit can be set on how much the template and the sample can differ to still be a match. This approach requires a twice as large template size, as both the mean and the variance of the feature vector components must be stored [2].

Several different distance metrics are explored in [1]. In addition to the Euclidean distance (as in eq. 3), absolute distance is tested, as well as Euclidean and absolute distances weighted by the variance:

$$\begin{array}{rll} \text{Absolute distance:} & \sum_{j=1}^{d} |y_j - f_j| & < \epsilon_a \\ \text{Weighted absolute:} & \sum_{j=1}^{d} \frac{|y_j - f_j|}{\sigma_j} & < \epsilon_{wa} \\ \text{Euclidean distance:} & \sqrt{\sum_{j=1}^{d} \frac{(y_j - f_j)^2}{\sigma_j}} & < \epsilon_e \\ \text{Weighted Euclidean:} & \sqrt{\sum_{j=1}^{d} (y_j - f_j)^2} & < \epsilon_{we} \end{array}$$

The threshold values for each respective distance metric are ϵ_a, ϵ_{wa}, ϵ_e and ϵ_{we}, the variance of the jth feature is σ^2, and y_j and f_j are the features associated with the claimed identity and the identity stored in the database [1].

In [6] the comparison is done by computing a normalized correlation between sample and template feature vectors. If the correlation exceeds a predefined threshold, the identity indicated by the user is verified. Otherwise the user is assumed to be an impostor. In the bimodal system, the two biometrics are combined using information fusion, i.e. in practise the two different types of feature vectors are concatenated and used as one long feature vector. Instead of this fusion at representation level, fusion at decision level can be used, i.e. separate hand geometry and palmprint scores can be combined to form a final decision score. Decision level fusion with max rule, i.e. using the higher of the two match scores as the final score, gives better results in [6] than representation level fusion.

Generally, any pattern recognition technique can be used to classify samples of hand images. Gaussian Mixture Models (GMM) are found to be an accurate method of computing the probability of a sample belonging to a class in [2] and [8]. GMM is based on modeling the patterns with a given number of Gaussian distributions, and is implemented with neural networks. The GMM hand geometry results achieved by Sanchez-Reillo [8] can be seen in table 1. The GMM neural network model performs clearly better than previous work based on Hamming Distance. Also Radial Basis Function networks are an option, but to train one user's network in a verification system, a database of other users' templates must be used, which can be against confidentiality restrictions in some systems [2].

The small template size and the reasonably simple computations needed for hand geometry enable novel approaches to storing and processing the templates. Sanchez-Reillo and Gonzalez-Marcos introduce in [10] a system, where the hand geometry data can be stored and also processed on the user's own smart card. This improves security, as the templates never have to be extracted from the card, or stored in any central location. In this approach the hand is in a sense the PIN associated with the card, as opposed to using a PIN code to identify yourself to a verification based access control system.

No. training vectors	3	4	5
Recognition (GMM)	88%	93%	96%
Auth: EER (GMM)	9.2%	7.0%	4.9%
Recognition (HD)	75%	82%	87%
Auth: EER (HD)	14.8%	10.4%	8.3%

Table 1. Results of hand geometry tests is [8]. Recognition success rates and Authentication Equal Error Rate for Gaussian Mixture Models and Hamming Distance system. Performance improves slightly with increased number of training samples, i.e. increased number of images grabbed during enrollment of the user.

4 Case studies

4.1 Identimat

One of the very first commercially used biometric systems was the Identimat, based on hand shape and finger length measurements. Its use pioneered the application of handgeometry and biometric technlogies in general [11]. The first Identimat was installed in a time-keeping system of a Wall Street investment firm, and in the 1970s at several highly secure facilities, for example in nuclear weapon industry [12]. Identimat technology was planned to be used at the 1980 Moscow Olympics to protect American athletes, but the USA boycotted the games [13].

4.2 RSI HandReaders

The Recognition Systems, Inc. (RSI), a company division of Ingersoll-Rand, is the leading producer of hand geometry technology. In the 1990s their ID3D Handkey was used for example to protect children at a daycare centers from unauthorized visitors, to control access to airport operations, and to track use of university students' meal plans [12]. For example at the University of Georgia access to the cafeteria was restricted to the 4000 students enrolled in its meal plan [14]. The only complaints about the system came from some people not willing to place their palm where so many others have placed theirs, i.e. keeping the platform clean was essential.

The need for access control is high in prisons, and consequently biometric handreaders are installed in many prisons. Both in Europe and America prison authorities are using hand geometry to check visitors [15]. For example prisons in Northern Ireland use HandKey systems. The first applications were installed in the Young Offenders Centre in Belfast in 1994 [16].

In the 1996 Atlanta Olympics, RSI hand geometry systems were integrated with the Olympic Village security system to process millions of transactions [17]. RSI HandReaders are also a part of the BASEL system designed for people crossing the Israeli/Palestinean border daily. Hand geometry is integrated with face recognition to secure the border crossing [18].

The verification rules used in the HandKey applications are variable, with adjustable sliding threshholds, which can be set either globally per reader, or on an individual user basis, depending on the balance between ease of use and absolute security. The system also uses reaveraging, i.e. updates the template to be an even closer match with the verified hand [15].

RSI Biometric HandReaders are currently widely used in access control applications, for example at more than half of the nuclear power plants in the US [17], and HandPunches in controlling time and attendance [19]. The user of a system, for example an employee, who is arriving at or leaving his workplace, places his hand on a scanner that records more than 90 measurements (lengths, widths, thickness, surface area, but not fingerprints, lines or scars). A 9-byte mathematical feature vector is computed from the measurements, and the comparison for a match or reject takes less than a second. The systems require no cards or badges, but ID or PIN numbers are used A HandReader device can be seen in figure 7.

The most recent pressrelease by RSI reports that a North Carolina hospital is increasing the security of its patients and 3500 employees by using HandReaders [20]. The birth center, where there is a perceived need for higher security, has used HandKey readers already since the mid-1990s. The security director at the hospital claims that not a single unauthroized person has gotten past a hand scanner.

In 1991 the Sandia Laboratories evaluated different biometric systems, and found that the RSI hand geometry technology performs very well. The False Accept and False Reject Rates naturally vary as the user adjustable threshold for acceptance is changed, but the equal error rate was 0.2% compared to the second best 1.5% of the EyeDentify Retinal Scanner. Hand geometry also clearly outperformed other biometric systems in user acceptance. Subjective questions about the ease of using the different systems achieved a ratio of 16 positive responses against one negative response, whereas other systems got at most one positive response per negative response [21]. The data for the tests were collected by having about 100 test subjects use different biometric devices daily for several monts. Later testing of further developed HandReader technology by the same laboratory gave 0.1% as the crossover False Reject and False Accept Rate [17].

Fig. 7. The HandKey access control device by Recognition Systems Inc.

4.3 INSPASS

The INSPASS (INS Accelerated Service System) is a hand geometry-based automated inspection system used at airports in the USA [22]. The system is based on RSI technology, i.e. there are HandReaders installed in self-service kiosks, where frequent business flyers can check themselves in to avoid long immigration lines [23]. The main objective with the system is to avoid checking the same business travellers repeatedly. Registered INSPASS users get a so called PortPASS card, which they carry along to present their identity at the INSPASS kiosks. Their hand geometry features are checked against the database template to verify, whether the person is owner of the card. Processing times are typically 15-20 seconds. The system is currently free of charge, and an enrollment is valid for a year at a time. If the card is expired or there is some other problem with the transaction, the INSPASS kiosk directs the traveler to an Immigration Officer [24]. INSPASS kiosks are located at large international US airports, and in Toronto and Vancouver in Canada, and the program is available for citizens of the US, Canada and Bermuda. Canadians also have their own similar system, the CANPASS, which is, however, based on different biometrics (iris recognition).

4.4 Finger Geometry at Disney World

The hand geometry business is clearly dominated by RSI's HandReaders. The only major implementation by another vendor, Biomet Partners, is verification of season pass holders via two-finger geometry at Disney World. The system is designed for convenience, as season pass holders can circumvent the long lines, but it is also a deterrant, preventing people from lending their season passes to friends [25].

5 Conclusions

Hand geometry techniques are simple, easy to use and inexpensive. The main disadvantage is its low discrimination capability, as hand geometry information may change during the lifespan of an individual [3]. Also the physical size of a hand geometry based system limits its use in som applications, such as laptop computers. The acceptability of hand geometry systems is high, perhaps because shaking hands is common behavior. Even though using the systems is easy, developers have found that the best way to reduce false rejections is to train people in using the machines [12]. Perhaps a typical user error causing a false reject can be seen in figure 8.

The fact that hand geometry is considered accurate enough only for verification but not for identification can actually be an advantage is some applications. In many access control applications, like immigration and border control, very distinctive biometrics may violate an individual's privacy [1].

The main difficulty in researching the material for this review was conflicting information. Most sources described hand geometry as a biometric that is user friendly but not accurate enough for high security applications. However, the experimental data, for example the Sandia Laboratories report, claim hand geometry to be an excellent biometric, better than any others in the same tests. My guess is that this conflict is a result of the identification versus verification dilemma. Hand geometry may not be accurate enough for identification, at least in a system with a large amount of users, but the verification accuracy is very high. However, the high results in verification can partly be explained by the way the tests were designed. For example, an evaluation of INSPASS data [26] was done with the assumption that there were no impostor transactions. I do not see how any false matches at all could be recorded under those terms.

Another problem was that a large part of the information available was commercial, containing presentations of hand geometry products on the market.

Fig. 8. An example of incorrect hand placement from [1]

Understandably the companies producing the systems do not reveal the actual algorithms behind the products, i.e. the scientific pattern recognition basis for this review was limited. Some scientifically tested methods are described in publications, but for example the applications by Jain et al [1] and Sanches-Reillo et al [2] are from the past few years and still for example the RSI HandKeys have been in use already in the early 1990s. Jain et al actually motivate their research by the fact that hand geometry systems are widely used, but still there is not much public literature addressing the underlying research issues [1]. Also the performance results achieved with the market leading RSI technology are much higher than the results presented in research articles. A partial explanation must be the vast resources the industrial developers have to fine tune and test their systems, but still it would be interesting to know what algorithms are behind the superior performance of RSI HandReaders.

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