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A survey of biometric technology based on hand shape

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ABSTRACT

Automated biometric systems have emerged as a more reliable alternative to the traditional personal identification solutions. One of the most popular biometrics is hand shape due to its ease of use, non-intrusiveness and public acceptance. This paper presents a survey of the technology used in hand shape-based biometric systems. We first review the component modules including the algorithms they employ. Next we discuss system taxonomies, performance evaluation methodologies, testing issues and US government evaluations. A summary of the accuracy results reported in the literature is also provided. We next describe some of the commercial hand shape biometric systems as well as some recent successful deployments. Finally, we mention a few limitations of the hand shape biometric and give some directions for future research.

1. Introduction

Automatic human identification has become an important issue in today's global information society. Due to increasing security concerns, a large number of systems currently require positive identification before allowing an individual to use their services. During the last decade, there has been a steady research effort[1] towards providing user-friendly and reliable methodologies for access to facilities, resources, services or computer systems. Biometric systems are already employed in domains that require some sort of user verification. It is generally accepted that physical traits like iris, fingerprints and, as more recently debated, hand shape and palmprints can uniquely define each member of a large population which makes them suitable for large-scale identification (establishing a subject's identity) [10,22,50]. On the other hand, in many small-population applications, because of privacy or limited resources, we only need to verify a person (confirm or deny the person's claimed identity). In these situations, one can also use behavioral traits[2] which have less discriminating power such as voice, face, signature and human–computer interaction (HCI) derived patterns.

Comprehensive reviews have been recently published on fingerprint [31], palmprint [50], face [49] and behavioral HCI [46] biometric technologies. In this paper, we survey the state of the art in hand shape-based biometric technology and complement the information provided in [10,36]. We also describe some of the commercially deployed systems and analyze the practical issues concerning enrollment, training and performance evaluation to consider when designing such systems.

Hand shape biometrics is the ensemble of techniques employed in establishing the identity of a person using person's hand silhouette and/or geometric features (e.g. finger lengths, widths, areas, ratios, etc) derived from it. In the biometric literature, hand shape systems usually include *all* systems using information extracted from a hand silhouette, while hand geometry refers to only those systems which use sparse geometric features. A typical hand shape biometric system uses a camera or scanner-based device to capture the hand image of a person and compares this against the information stored in a database to establish identity. Besides person identification, hand imaging has also been used for deriving statistical models of biological shapes [14] and for guiding gesture-based HCI tasks [43].

As often noted in the literature, hand shape biometrics is attractive due to the following reasons:

1. Hand shape can be captured in a relatively user convenient, non-intrusive manner by using inexpensive sensors [2,25,30].
2. Extracting the hand shape information requires only low resolution images and the user templates can be efficiently stored (nine-byte templates are used by some commercial hand recognition systems [35]).
3. This biometric modality is more acceptable to the public mainly because it lacks criminal connotation [16,24].

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[1] As noted in [10], the number of publications on hand-based biometrics has increased almost exponentially since 1998.

[2] In reality most biometrics are both physical and behavioral to some degree.

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4. Additional biometric features such as palmprints and fingerprints can be easily integrated to an existing hand shape-based biometric system [10,25,30].

2. Operation of a hand shape-based biometric system

A hand shape-based biometric system operates according to Fig. 1. In the enrollment stage, hand shape data are acquired from the registered users, feature sets are extracted from the acquired data, and one or multiple templates per individual are computed and stored in a database. In the deployment stage, one snapshot of the user's hand is captured, a feature set is computed and then compared to the templates in the database. Based on the comparison result, the claimed identity is accepted or denied (or a new identity is assigned). The identification system comprises the following modules: the sensor module, the feature extraction module, the matching module, the decision-making module and an optional template adaptation module.

2.1. The sensor module

Starting with Sidlauskas' patent [34], the sensor has usually been a low/medium resolution CCD camera attached (beneath or above) to a platform on which the hand is placed (Fig. 2(a)). Most system setups provide their own illumination rather than rely on the ambient light. A recent study proposed using infrared light for better hand segmentation in an unconstrained, real environment [29]. Some multimodal biometric systems capture the palm surface which includes both the hand shape and palmprints [10,25,30]. Other systems capture the dorsal surface of the hand from which only the hand silhouette can be extracted (see Fig. 2 and [13,20,21,34]). The lateral hand surface can be captured as well on platforms with a side-mounted mirror inclined at 45° to the platform [21,30].

Most commercial systems [4,34,35] and some of the research systems [13,20,21,25,33] include on the platform 4–6 pins to guide the placement of the user's hand. Several researchers noted that the guidance pins deform the hand silhouette and decrease user convenience and proposed pin-less setups [1,2,8,10,40,45,47,48,51]. In a few systems, the sensor consisted in a 45–180 dots per inch (DPI) scanner [30,40,47,48] while a 3-D range sensor was employed in [41] to extract finger surface curvature features.

A recent trend in hand-based biometric systems is oriented towards a platform-free, non-contact image acquisition setup which responds to hygiene concerns and is considered more user-friendly [29,41,51]. However, such setups introduce additional variation in the images acquired and require sophisticate illumination (see the camera settings recommended in [29]) and/or image processing techniques in order to properly segment the hand from the background.

2.2. The feature extraction module

In the feature extraction module, a set of discriminating features is computed from a user's raw hand image(s).

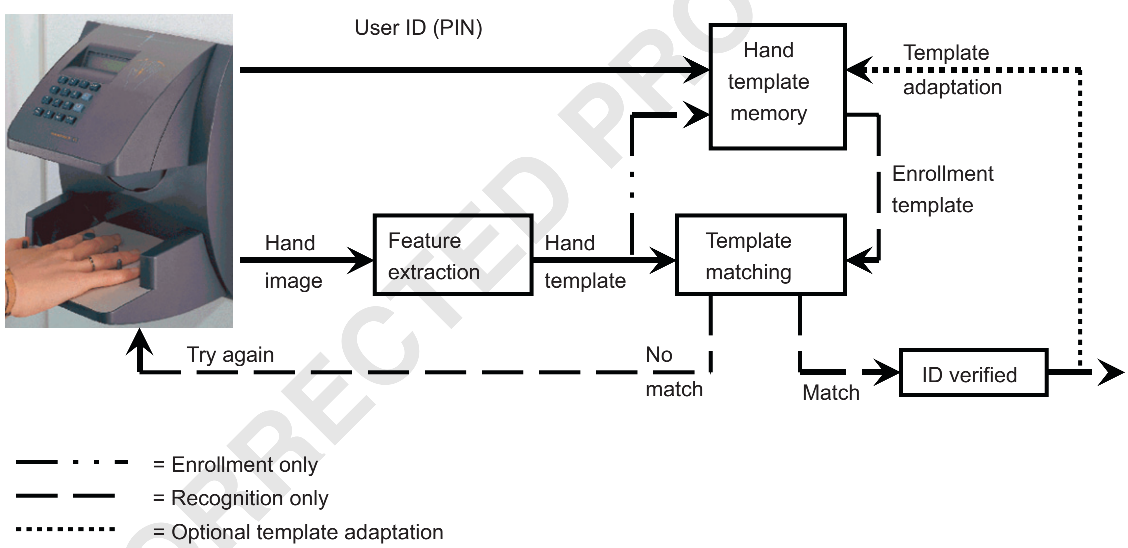

Fig. 1. Processing steps in an identity verification system using hand shape.

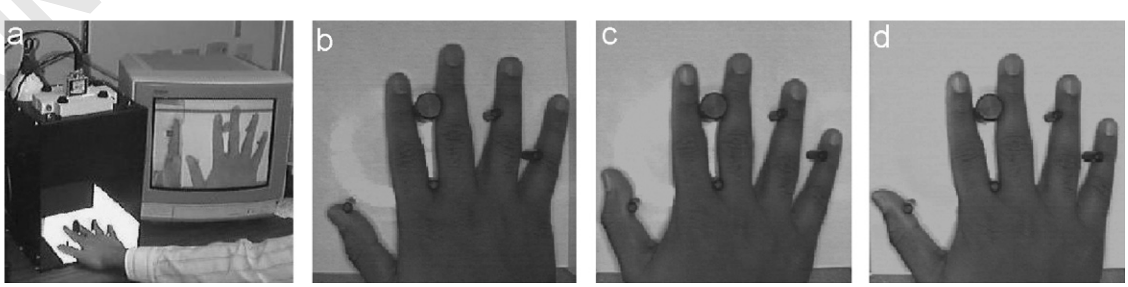

Fig. 2. Example of a hand shape image acquisition system along with three scans of the same hand.

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2.2.1. Image pre-processing

The hand images are first pre-processed in order to extract the hand silhouette and eliminate artifacts such as the guidance pins, user rings, overlapping cuffs or creases around the contour due to too light or too heavy hand pressing. The pre-processing step can range from simple image thresholding [2,8,13,25,30] and filtering [29] to sophisticate gray-level segmentation [20,47] or edge detection [21,33,51]. Possible dents at the artifact location are smoothed by linear interpolation [20,38] and/or morphologic operators [8] or are simply not used in the feature extraction process [29]. Hand images taken in a more constrained environment require simpler and faster pre-processing algorithms but that usually comes at the expense of a bulkier and more expensive acquisition device.

2.2.2. Hand silhouette alignment

In order to properly compare feature vectors extracted from hand images, one has to align the hand silhouettes such that each feature is computed from the same region of the hand. Most of the older systems relied on the pins to align the hand images. However, if the user is untrained or does not cooperate to properly use the hand scanner, then the resulting images are not aligned and the system's verification performance degrades [20]. Therefore, it is critical to automatically align the acquired hand shapes before extracting the feature vectors used for identification.

Due to the flexible nature of the palm and fingers, there may be no linear transformation which accurately aligns two hand silhouettes. Hence, many of the proposed alignment procedures detect and align each finger separately. The fingers can be easily extracted if they do not touch one another [8]. The simplest finger alignment method consists in registering the fingertip, the two adjacent valley points and several equally spaced points along the contour in-between the three landmarks [8,38]. Similarly, a Euclidean transformation can be found to align the finger symmetry axis [40,47]. A more sophisticated alignment procedure (based on quasi-exhaustive polynomial search of point pair matches between two sets of contour points) is presented in [20]. This procedure has the advantage of always finding a good alignment even if the valley-point landmarks are not accurately detected.

The alignment step can be avoided if the set of features extracted from the hand image is invariant to Euclidean transformations [2,51]. A combination of low computational, global hand alignment (called Natural Reference System) and semi-invariant feature set has been introduced in [1]. However, the authors assume a high degree of user cooperation such that the hand is fully extended in all images.

2.2.3. Feature sets

Among the most used feature sets are geometric measurements: length and width of the fingers, aspect ratio of the palm or fingers, hand length, thickness, area, etc. Geometric measurements based on point sets which are not hand landmarks [1] and 3-D surface curvature features (which attempt to model skin folds and crease patterns [41]) have also been proposed. The total number of geometric features has varied from 13 to 40 (see Table 1).

Some authors investigated shape-based feature sets. The hand shape can be modeled either explicitly as a set of (2-D) coordinates of several landmark points along the hand silhouette [20,38] or implicitly as a binary image of the hand over an empty background [2,10,47,48]. The two representations are intrinsically equivalent; each of them can be easily derived from the other. With both representations, dimensionality reduction procedures may have to be applied as the original data typically has a high dimensionality (see the fifth column in Table 1). The dimensionality reduction methods most used are principal component analysis (PCA) and independent component analysis (ICA) and are applied to either the original data or to a transformed version of the data (e.g. the Zernike moments in [2]).

Most of the time, the feature vector is computed based on the entire hand or a subpart (2–4 fingers) of it although the individual fingers may have been extracted and aligned separately. One or several templates per user may be created during the enrollment stage and stored in the system's database. The templates are either the raw feature vectors computed from a user's hand images or the average of those feature vectors.

2.3. The matching module

This module compares a user feature vector against the user's template(s) stored in the database in order to generate matching scores. Since the feature vectors are usually points in an N-dimensional Euclidean space, any metric distance can be used for computing a matching score: Euclidean distance [2,33], Mahalanobis distance [21,30], absolute (L1) distance [8,47], correlation coefficient [25,41], or a combination of those distances (in some multimodal biometric systems [30]). A few studies explicitly model the class-conditional probabilities under Gaussian assumptions and use them as matching scores [13,33,38,40]. As an exception [20,48], use the Procrustes shape distance and [47] uses a modified Hausdorff distance since the feature vectors are shapes corresponding to the hand silhouette.

The matching score is a positive number which shows the dissimilarity between the user's hand and the templates in the database. In some studies, individual fingers are matched separately and the matching scores are subsequently fused into a single score (see [41] for a comparison of several score-level fusion rules).

A different matching approach proposed in the literature consists in training a collection of two-class statistical classifiers (e.g. support vector machine—SVM) to predict a person's identity [29]. For each of the enrolled identities, a classifier is trained using as positive examples a set of feature vectors associated with the given identity while the set of negative examples consists of feature vectors drawn from all the other enrolles. In order to verify that a sample feature vector belongs to the identity claimed, the classifier trained to learn that identity is used to produce a matching score. In the SVM case, the matching score is the distance to the hyper-plane which separates the claimed identity from the other enrolled identities. While a classifier approach may have a better discrimination power, it also requires that a separate classifier is trained for each of the enrolled persons. For large-population systems, that may become a computational challenge.

2.4. The decision-making module

The final decision concerning the user's identity (identification) or the user's claimed identity (verification) is taken by the decision module. In verification mode, the decision is typically threshold based: if the matching score is below a given threshold the claimed identity is accepted, otherwise it is rejected. The threshold value is chosen such that the system satisfies some operating constraints (e.g. an upper bound on the false accept rate (FAR), an equal error rate (EER), etc). In identification mode, the incoming feature vector is typically assigned the identity of the closest database template if the distance to that closest template is lower than the verification threshold, otherwise the feature vector is consider to belong to an impostor.

2.5. The template adaptation module

The long term system performance can be improved by an optional template adaptation module which updates (by averaging for

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Table 1
Comparison of some hand shape-based systems presented in the literature.

Year system	Population size	Samples/person	Number/type of templates	Features used	Similarity measure	Performance
1997 [13]	100	8	1 (mean of a multinormal pdf)	Finger lengths/widths, thickness (17)	Bayes aposteriori class probability	EER = 0.0012
1999 [21]	50	5–10	1 (average feature vector)	Finger lengths/widths, aspect ratios (16)	Mahalanobis distance	FAR = 0.01 FRR = 0.17
1999 [20]	53	2–15	1–14 (raw contours)	Hand contour coordinates (120–350 contour points)	Mean alignment error	FAR = 0.01 FRR = 0.06
2000 [33]	20	10	1 (average feature vector)	Finger lengths, widths, ratios thickness, deviation (25)	Euclidian, Hamming, GMM	EER = 0.05
2002 [40]	22	12–15	2 (average feature vectors)	Finger lengths, widths (13) Fingertip coordinates (50–90)	GMM probability ratio of hit points	FAR = 0.022 FRR = 0.111
2004 [5]	70	10	1 (training vector bounding box)	Geometric features (30)	Nearest box (L_∞) minimum enclosing ball	FAR = 0.01 FRR = 0.03
2004 [30]	110 registered 399 impostors	7	3 (raw feature vectors)	Finger lengths/widths, palm width (24)	Normalized Euclidian distance	FAR=0.01 FRR=0.001[a]
2005 [38]	51	10–20	1 (average) + multiple raw	Hand contour coordinates, angles (51–211 contour points)	Log-Likelihood under Gaussian assumption	EER = 0.00001–0.002
2005 [8]	96	10	1 (average feature vector)	Finger lengths/widths (21)	$\frac{1}{d}\sum_{i=1}^{d}\frac{\min(yi-fi)}{\max(yi-fi)}$	EERVerif = 0.03 EERIdent = 0.06
2005 [41]	223	5–8	1 (average feature vector)	Shape indices (based on 3-D surface curvature) (18,500)	Normalized correlation coefficient	EERVerif = 0.09[b] ErrIdent = 0.15
2006 [47]	458	3	2 (raw feature vectors)	Contour coordinates (2048 points) ICA on binary hand image (458)	Modified Hausdorff L1, cosine distance	EER = 0.01–0.02
2006 [2]	40	10	5 (raw feature vectors)	Zernike moments of the binary hand image followed by PCA (30)	Euclidian	FAR = 0.01 FRR = 0.02
2008 [1]	470	6–8	1 (time averaged feature vector)	Non-landmark based geometric measurements (14 for each hand)	Normalized sum of feature deviation	FAR = 0.0045 FRR = 0.034
2008 [29]	20	10	4 (SVM training)	Finger widths for three fingers (40)	SVM score (distance to separator hyper-plane)	EER = 3.4%

[a]The authors reported FAR/FRR rates for a system which combined hand geometry features with fingerprint and palm-based features.
[b]The authors only reported verification experiments corresponding to a 16-week lapse between the enrollment images and test images.

example) a user template after each successful authentication of that user. Thus, the system can accommodate slow changes in user's physiology due to hand swelling, arthritis and/or weight changes. The adaptation module is mostly present in the deployed systems [1,35].

3. Performance evaluation

3.1. System taxonomies

A biometric taxonomy is usually based on partitions which classify the usage of biometrics within a given application. The following taxonomies have been mentioned in the literature (biometric systems are considered to perform best when employed in the first five conditions of the left column) [32,39]:

- Cooperative vs non-cooperative user. (Are users willingly participating?)
- Overt vs covert biometric system. (Are users knowingly participating?)
- Habituated vs non-habituated user. (Are users familiar with the system?)
- Attended vs unattended system. (Is there any supervision when the system is used?)
- Stable environment vs unstable. (Are the environment factors changing with time?)
- Optional usage vs mandatory usage. (Are users required to use the system?)
- Public vs private. (Are the users customers of the system management (public) or employees (private)?)
- Open vs. closed system. (Is the system going to exchange data with other biometric systems?)

As noted in [39], "the taxonomy of the enrollment environment will determine the applicability of the test results". That is, not all results reported by research studies might be attained in a live application since the taxonomy may differ.

Almost all research systems fall into the overt, habituated, attended, stable environment taxonomy. Although most reports imply having cooperative users, the degree of user cooperation is sometimes questionable as some of them are "gaming" the system or trying to test the system's limits (see the discussion in [24] and

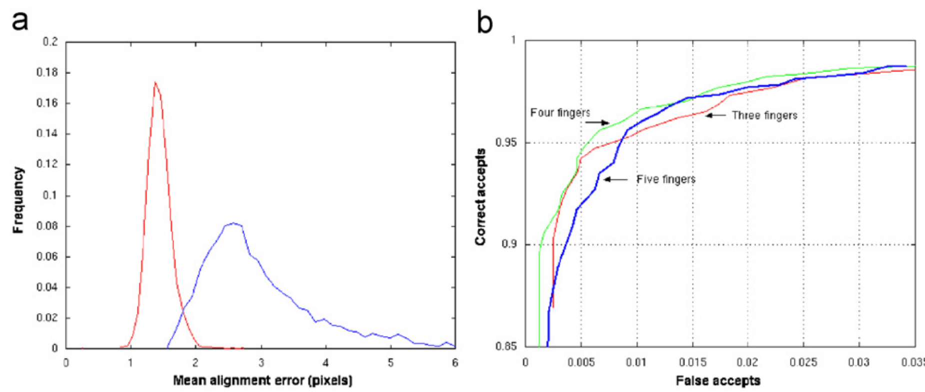

Fig. 3. (a) Mean alignment distance distributions for the genuine class (left) and impostor class (right) computed by using all fingers (from [20]). (b) ROC curves for the hand shape-based verification system described in [20]. The three curves correspond to feature vectors extracted from three, four and five fingers and one-try verification attempts (from [9]).

Section 5). In our opinion, that behavior induces a larger intra-class variation when the hand data are collected online in a deployed application vs. offline in a laboratory. The online university systems appear to experience the most intra-class variation. That can have a significant impact on system performance and makes it difficult to directly compare various technical approaches proposed in the literature. The commercial systems can have non-habituated (first time) users, are many times un-attended and can be both public and private (see Section 4 for examples).

3.2. Performance evaluation methodology

The performance of a biometric system can be tested in either an open-set or a closed-set paradigm. The closed-set testing assumes that only the enrolled users can access the system fact which can rarely be guaranteed in practice. The open-set testing allows the presence of unknown impostors and is typically performed by plotting the probability distribution of the matching scores corresponding to genuine (feature vectors acquired from the same user) and impostor (feature vectors acquired from different users) comparisons (Fig. 3(a)).

A biometric system can make the following types of errors: (i) a false accept when an impostor matching score is lower than the decision threshold, (ii) a false reject when a genuine matching score exceeds the threshold and (iii) an identification error when the assigned class of a feature vector is not the true class. Since the false accept and false reject errors depend on the decision threshold, a Receiver Operating Characteristic (ROC) curve is used to plot the FAR (the percentage of impostor scores that do not exceed the threshold) against the Correct Accept Rate (CAR—the percentage of genuine scores that do not exceed the threshold) at various thresholds (Fig. 3b)). One can equivalently report the False Reject Rate (FRR) which is equal to 1−CAR. The error rate at which the FAR equals the FRR is called EER and is sometimes used as a single-figure system comparison metric.

Biometric systems used in identification mode also report the Cumulative Match Curve (CMC) which plots the cumulative recognition rate as a function of recognition rank. If closed-set testing is used, no score distributions are estimated and no decision threshold is needed.

In the past, the US government sponsored two evaluations of hand geometry technology. In the 1991 performance evaluation of biometric identification devices, multiple biometric systems were evaluated to establish their relative performance. Among biometric technologies, hand geometry was found to have the highest user acceptance of all devices tested. The Recognition Systems Inc (RSI) hand scanner ID3D-U exhibited a 0.2% EER[3] and a 5 s verification time [16]. The 1996 evaluation of the INSPASS (Immigration and Naturalization Service Passenger Accelerated Service System) hand geometry data[4] determined the effect of a threshold on system operation, established false accept and FRRs as a function of the threshold, and presented an estimate of the system's ROC curve. The EER of the INSPASS test system was estimated to be less than 3%[5] in an application which could be classified as "cooperative, overt, non-habituated, non-attended, stable environment" [39].

For the more recent research systems, performance evaluation can only be based on the results and comparisons provided by their authors. Several enrollment and performance evaluation methodologies are discussed in [38,41]. If extensive enrollment data can be acquired, best performance is attained when an average template is computed from each user's enrollment measurements. However, such a system is less user-friendly and more difficult to deploy. A more realistic deployment scenario requires only one to three enrollment measurements per user. In such case, a template may actually be a raw feature vector and the main system parameter to estimate is the decision threshold. Most researchers split the available measurements for each user into an enrollment set and a testing set and evaluate the threshold value based on the enrollment data. This has the advantage that the training data are representative for the test data. That is, one expects to obtain an estimate of the decision threshold which works as well on the test data. In commercial deployments though, the system may be trained by the manufacturer while the enrollment is performed by the customer who has to use the factory set threshold.

3.3. Evaluation issues

It is difficult to directly compare the performance figures reported in the literature. The main reason is the absence of:

(i) A standard data acquisition setup: there is some variation in the image quality due to camera positioning, camera resolution, illumination, etc.

[3] Based on tests employing two hand readers, a total of 10,588 genuine and 9087 imposter transactions and a single, fixed threshold. The error rate was quite low most likely due to PIN entry by magnetic card reader rather than by keypad.

[4] This data was also acquired with RSI ID3D hand scanners operated by the contractor EDS.

[5] Based on 1769 genuine and 4.3 M imposter hand template comparisons. The imposter distribution was simulated out of 2946 hand templates as it was assumed that no imposter transactions were actually attempted in the deployed system.

(ii) Standard enrollment and testing procedures: there is some degree of variation in the enrollment paradigms, number of templates stored and whether template adaptation is performed. Although biometric experts seem to agree on using an open set testing approach for verification purposes, there is still some controversy on when to use an open set vs. a closed set testing in an identification task [37].
(iii) A common benchmark data set.

The different test datasets introduce several variation factors in the systems reported:

(i) Population size: ranging from 20 to over 1000 persons.
(ii) Population age and/or structure: most research datasets are based on college students, while the commercial data may come from frequent travelers, visitors, employees, etc.
(iii) Users' training and/or motivation to cooperate: users may become habituated with the system and adjust their behavior over time thus reducing the error rates. Or, if the system is attended and the failed identification transactions are investigated, the users' motivation to cooperate is likely to increase.
(iv) Timeline: many research studies collect data over a relatively short period of time while data used by deployed applications may be months or years apart.

These aspects are well discussed in [1] where several research algorithms were re-implemented and tested on hand data obtained in a deployed system. The authors were not able to reproduce the originally reported accuracy results for any of the re-implemented algorithms, some of which showed significant degradation. The degradation was attributed to two factors:

(i) Different population structure: the deployed system used a very homogeneous teenager (15–17 years old) population (the age/job similarity is assumed to decrease inter-class variation and make the identity discrimination task more difficult).
(ii) Most literature systems have become quite sophisticate and it is more difficult to re-implement them exactly.

One should note though that the system described in [1] monitored high-school student presence in an attended, closed-set scenario. Therefore, gaming and impersonation were probably never attempted. In such cases, the intra-class variation is also small and compensates for the small inter-class variation.

3.4. Performance review

Table 1 summarizes the performance of some research systems[6] tested in identity verification mode. Some authors only report EER figures while others include the system ROC curve. When the ROC curve was present, we estimated the FRR rate corresponding to FAR = 0.01. As it can be seen in the last column of Table 1, most systems reported error rates on the order of 10^{-2}. For comparison, the Scott AFB hand shape-based access system (see Section 4) operated at a FRR = 0.0269 with no false accepts [42]. However, the Scott AFB system combines hand shape biometrics with a PIN and it is unlikely that it had to handle many impostor requests. All verification procedures discussed above can be performed within one second using today's computers.

A few systems have also been tested in identification mode and report top-rank identity recognition errors of 1–6% [5,8,33,47]. Some authors integrate hand shape features with fingerprint and palm-based features (which can be acquired through a single image measurement) and report verification error rates on the order of 10^{-3} [25,30,48].

Few studies document the impact on the system performance of factors like population size, amount of enrollment data per user, time lapse, image quality, using features extracted from both hands, etc. The most comprehensive discussions of such factors we are aware of can be found in [10,41] and can be summarized as follows:

(i) Top-rank identification accuracy with two enrollment images per user and a population size of 50 is around 98% [10] and decreases only slightly (about 1% absolute) when the population size increases to 918.[7]
(ii) Using two enrollment images per user instead of one, significantly decreases the identification error (70% error reduction reported in [10], 20% reported in [41]).
(iii) Using left hand features gives a slightly better accuracy than right hand features (0.3–0.5% absolute [10]).
(iv) The index, middle and ring fingers appear to be equally good for discrimination [41].
(v) Time lapse (2 weeks–3 years) appears to have little impact on system performance.[8]
(vi) Images with a resolution as low as 30 DPI could be used without significant performance degradation [10].

4. Deployment history

Hand geometry appears to be the oldest automatically employed biometric modality as hand geometry-based systems have been commercialized for almost four decades [36]. These systems accounted for 4.7% (141 million US dollars) of the world revenues generated by all biometric modalities and were the fourth leading biometric technology in 2007 [18]. The technology has evolved from stand-alone electro-mechanical devices in the early 1970's to today's electronic scanners attached to powerful computer systems with access to a central database.

The first commercial hand geometry scanner, called Identimat and based on Miller's patent [28], was manufactured by Identimation from early 1970's to 1987. This device consisted of a hand platform illuminated by an overhead 1000 W lamp along with an attached magnetic stripe read head for reading user's ID card. The platform contained a four-slot hand template where the hand was placed palm down with the fingers aligned by a central pin and two separator plates (Fig. 4(a)). Mechanically scanned photocells, placed underneath the four finger slots were used to measure the finger length, endpoint contours and translucency of the skin. If the measurements matched the template on the user's ID card within a threshold, the user's identity was verified. Although other patents were filed at the same time for hand-based identification devices [12,23], the Identimat was the only one which passed the prototype stage.

In 1986, Recognition Systems[9] launched a new generation hand recognition scanner (ID3D HandKey) based on Sidlauskas' patent

[6] This selection attempts to representatively sample the literature chronologically as well as according to the system characteristics (image acquisition setup, feature type, similarity distance used for matching, size/structure of the enrolled population, reported accuracy, etc.).

[7] This result applies to the pure shape-based system. The remaining results were only given for the shape + appearance system but, we believe, could be extrapolated to a shape-only system.

[8] One should take into account that the population used was mostly students.

[9] Recognition Systems is currently the biometric division of Ingersoll-Rand Corporation.

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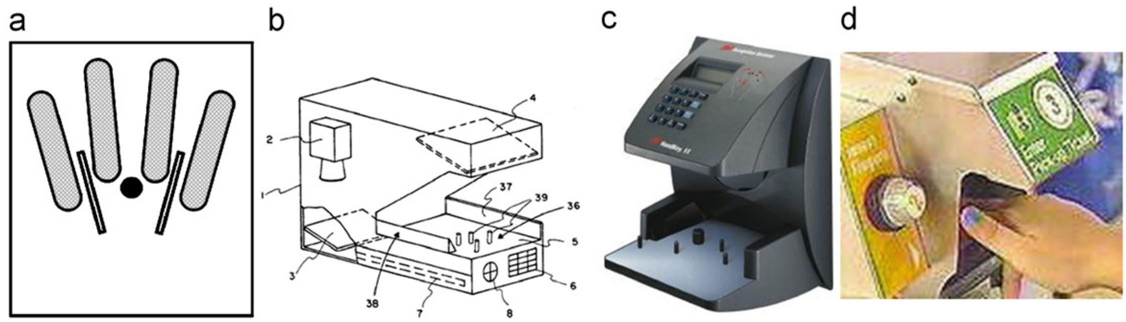

Fig. 4. Commercial hand geometry scanners. (a) Schematic drawing of the Identimat platform, (b) Sidlauskas' patent drawing [34], (c) The HandKey II scanner from Recognition Systems, and (d) Finger geometry reader at the Walt Disney World entrance gates.

(Fig. 4(b)). It used a peg-based setup and a CCD camera optimized to capture a binary image of both the side (with the help of a side view mirror) and top views of the hand. Over 90 hand geometry features were estimated from the hand silhouette images and dimensionality reduction techniques (PCA like) were applied to compute a nine-byte[10] vector of independent features. The first HandKey devices included Z-80-based microprocessors, and memory which could store up to 20,000 user templates. The ID3D could also accommodate magnetic card reader emulation which enabled it to be easily connected into existing access control systems [36]. As such, it provided a complete solution to access control and attendance applications.

The first applications for hand scanners controlled access to various government, nuclear and military facilities. The emergence of low cost acquisition devices as well as high speed mobile processors made it possible to produce hand shape-based biometric systems affordable in the commercial access control market. Due to application constraints, limited computational resources and/or privacy issues, all commercial hand shape biometric systems we know of operate in verification mode; that is the system confirms or negates the claimed identity of an individual. Among the more recent successful deployments one can mention:

(i) The system used to control physical access to the Olympic Village in the 1996 Olympic Games. More than 65,000 people were enrolled and over 1 million transactions were handled in 28 days using HandReader II devices [6].
(ii) The INSPASS program which facilitated the entry of over 50,000 pre-screened low-risk travelers through immigration and customs at certain airports. This identity verification system, also using HandReader devices, was deployed at the JFK, Los Angeles, Miami, Newark, Toronto and Vancouver international airports in 1990's. The INSPASS system made "accept/reject" decisions on the basis of a maximum of three entry attempts by the user. INSPASS was the first large-scale biometric identity verification program undertaken by the United States Government [17].
(iii) The Walt Disney World "two-finger" geometry system expedited entrance to the park and prevented season ticket fraud. This system used a Biomet Digi-2 device and performed over 20 million verifications while in use at Walt Disney World [4].
(iv) The system controlling access to the Scott Air Force Base through its MetroLink rail station entrance. This is based on a combination of personal identification number (PIN) and hand geometry biometrics obtained using a HandKey II device and enrolled over 10,000 users [42].

One can also note the standardization efforts focusing on hand geometry technologies which resulted in the international standard[11] ISO/IEC 19794-10 Hand Geometry Interchange Format defining the format for storing, recording and transmitting hand geometry data in a nonproprietary silhouette format [19]. This standard defines the content (e.g. data capture parameters, standardized hand position, vendor-specific information), format (e.g. (x, y) coordinates compressed using a Freeman chain code), and units of measurement for the exchange of hand silhouette data.

As a final remark, all current commercial systems we are aware of are only using a small set of geometric measurements as opposed to the full shape of a user's hand. This is due to computational and storage requirements, but may change in the future as processors and storage become faster and cheaper.

5. Issues and limitations of the hand shape-based biometric approaches

5.1. Hand shape uniqueness

The issue of hand shape uniqueness within a large population is currently somewhat controversial. Some researchers and designers of commercial biometric systems consider hand shape to have a medium-to-high discrimination power [30,32]. On the other hand, the authors of some recent research systems [10,47,48] have shown high verification/identification rates which are comparable to fingerprint-based systems. However, their datasets appear to be collected offline and have, arguably, smaller intra-class variation since: (i) the data acquisition environment is highly controlled and therefore, less noisy and (ii) the behavioral issues of a live biometric system (user gaming and impostor requests) are missing. Even if the hand shape is indeed unique within a large population, it might not be always feasible to extract it very accurately in real deployment environments [41].

5.2. Other factors influencing the accuracy of a hand shape biometric system

Several additional factors influence the effectiveness of hand shape biometrics:

(i) The human hand is a flexible object and its silhouette may suffer non-linear deformations when multiple hand images are acquired from the same person. That is especially true when users

[10] In order to decrease the FAR, the template size was recently increased to 20 bytes.

[11] A similar (although not binary compatible) US national standard proposal (ANSI INCITS 396-2005) has been recently withdrawn [3].

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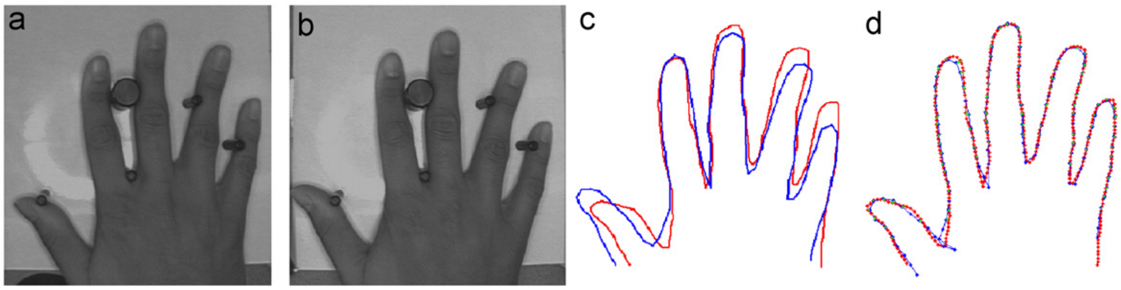

Fig. 5. Two hand scans of a non-cooperative user [20]: (a, b) original images, (c) hand shapes extracted from (a) and (b) overlaid, and (d) finger aligned shapes (mean alignment distance = 2.20 pixels).

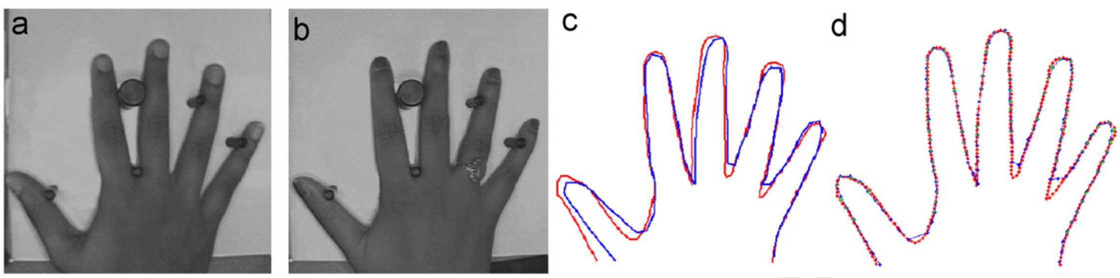

Fig. 6. Two hand scans of different users [20]: (a, b) original images, (c) hand shapes extracted from (a) and (b) overlaid, and (d) finger aligned shapes (mean alignment distance = 2.02 pixels).

are untrained, non-cooperative or are gaming the system and was pointed out in [20,21] and more recently in [24]. Improper thumb placement and little fingers that would not straighten were found by [24] to generate statistically significant differences in matching scores. That is also shown in Fig. 5 where a user's thumb appears to be longer in one of the images and it generates a high mean alignment distance (2.2 pixels). That distance is higher than many of the distances corresponding to impostor matching (see Fig. 3(a)) and makes the system reject its true identity. This problem is alleviated if the thumb (which can deform more than the other four fingers) is excluded from the feature vector calculation. Fig. 3(b) (reproduced from [9] and based on the system described in [20]) compares the ROC curves corresponding to using all fingers vs. excluding the thumb and/or the little finger. The system which excludes the thumb exhibits a substantially better performance over the system which uses all fingers: 2–5% absolute increase in CA rate at a FA rates smaller than 1%.

(ii) It has been noticed in several biometric systems [11,15] that the identity models for some users are systematically better (or worse) in authentication performance than the models for other users. That is, every person apparently has his own error rate and can be more or less difficult to impersonate. This phenomenon has been exemplified by the so called Doddington's Zoo [11] which showed the existence of persons very vulnerable to impersonation (called "*lambs*") at the same time with persons very successful at impersonating others (called "*wolves*"). We believe this phenomenon is present in hand shape biometrics as well: during our experimentation with the system in [20] we identified a "*lamb*" within a population of 53. In Fig. 6, after finger alignment, the hand silhouettes of the two users are almost identical. Therefore any geometric features extracted from the two aligned silhouettes will be very similar and the system will likely confuse the identity of the two persons. However, the problem is alleviated if the system is used in verification mode since it is unknown to the users whether there are any "lambs" (or who they are) in the enrolled population.

(iii) Chen et al. [7] showed that hand shape systems are vulnerable to spoof attacks. They built fake hands out of silhouette images captured by a HandKey II hand geometry reader and had them accepted by the system.

5.3. *Author's experience with system deployment and behavioral issues*

Our experience with a research hand-based biometric system can be summarized as follows. The system was originally built at Michigan State University as described in [21]. It was fully deployable, that is, it included a self-contained image acquisition device and a graphical user interface (see Fig. 2(a)) which performed live user enrollment and one-try identity verification. However, it was not really deployed in the sense that its identity decisions were not used to take any action, but rather demonstrate the idea of biometric authentication.

The enrolled population was mostly students 20–30 years old, who volunteered to test the system. However, several users were more interested in probing the system's ability to handle situations where the user wore jewelry, had painted nails or their hand was misplaced on the acquisition device. Those users tested whether the system would still accept a genuine request or still deny an impostor request in such non-standard situations. Such behavior generated a large amount of intra-class variation and decreased the system's performance.

This problem was acknowledged in [20] which reprocessed off-line all hand images previously acquired (over a 2–3 months time period, though not in a systematic regular way) in order to accurately align each pair of corresponding fingers and compute a matching score based on a continuous shape distance rather than on a small number of geometric measurements. The system performance increased significantly, but there were still issues with the thumbs

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which could not be properly aligned due to non-linear deformations. Therefore, we proposed to omit the thumb in the hand matching process and showed that the accuracy further increases (see [9] and Fig. 3(b)).

5.4. Applications suitable for hand shape biometric technology

Commercial systems have traditionally used hand shape biometrics only in identity verification mode and many times in conjunction with a PIN [42] or magnetic stripe card [4,35]. Due to its perceived lower-discrimination power, the application range was limited to low–medium security, mostly access/attendance control applications. However, recent research suggests that hand shape could be used to produce very accurate short identification lists ([1,10,47,48] report top 10 identification errors smaller than 0.5% on populations of up to 1000 people) and even reasonable (1–2%) top-rank identification errors. Although the identification results are quite promising, the fact that the hand shape cannot be easily obtained in a covert way (like for example, the human face can be recorded by monitoring cameras) or is rarely found in forensic situations will likely continue to limit its application range.

6. Future directions

Hand shaped-based authentication systems have been widely used for applications in access control, attendance tracking and personal identity verification for almost 40 years. However, this is still an active area of research which focuses on:

(i) Designing an unconstrained hand image acquisition setup, in which no guiding pins or even a platform are needed. That can be achieved by using different illumination [29], multi-modal sensors (e.g. combined 2-D and 3-D range [41]), sophisticated silhouette alignment [10] and/or feature sets which are invariant to hand positioning [1,2,51].
(ii) New approaches to feature matching (e.g. employing a classifier [29]) and finger score fusion [1,41].
(iii) Fusing hand shape with palmprint features into "hand appearance" models [10,30]. Using palmprints has the advantage of requiring only a slightly modified image acquisition setup as opposed to adding a new sensor for other biometric modalities. Employing the full hand shape and palmprints as discriminating features appears to improve the authentication accuracy by a order of magnitude and makes hand-based systems suitable for identification applications. Multimodal biometric systems are also more robust to fraud attempts.

At this time, there appears to be a gap between the technology used in research systems and that used in commercial systems. We believe it is most likely due to a combination of high computational requirements of the current research approaches and a lack of small-sized, reliable image acquisition setups. That makes many algorithms relatively hard to deploy in a real world environment. More specifically, the research technology reportedly works on off-the-shelf computers but very little has been designed to work and tested in hardware or on mobile devices (see [26] for one of the few hardware implementations). We are also aware of a single research system [1] which has actually been deployed and had to handle technology issues not encountered in off-line systems: continuous availability, adaptability to time changing measurements, robustness to gaming and/or impostor requests. This technology gap will likely narrow in the near future as cheaper and more powerful mobile processors enter the market and more research systems will be deployed.

7. Uncited references

[27,44,52]. Q2

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