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Hand Geometry Techniques: A Review

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***Abstract*— Biometrics is used for identification and verification of individuals using their physical or behavioral characteristics. Biometrics has gained importance in today's world where information security is essential. Automated biometric systems have emerged as a more reliable alternative to the traditional personal identification solutions. Hand geometry, one of the most well-known biometrics, is implemented in many verification systems with various feature extraction methods. It is one of the most popular biometrics due to its ease of use, non-intrusiveness and public acceptance. Hand geometry based biometric systems are used in the applications where low to medium security is required. Hand biometrics is extensively used for personal authentication**

***Index Terms*— Biometric authentication, Hand Geometry, False Rejection Rate, False Acceptance Rate.**

I. INTRODUCTION

A. Biometrics

Biometrics is one of the automated methods for identification or verification of a person based on a physiological or behavioral characteristic. Biometric authentication system requires comparison of a registered or enrolled biometric sample/template with a newly captured biometric sample. During enrollment a sample of the biometric trait is captured and processed by a computer, and stored for later comparison. Biometric recognition can be used in identification mode, where the biometric system identifies a person from the entire enrolled population by searching a database for a match based solely on the biometric. A user enters an account, user name, or inserts a token such as a smart card, but instead of entering a password, a simple touch with a finger or a glance at a camera is enough to authenticate the user [1].

B. Working of Biometric Technologies

At their most basic level, biometric technologies are pattern recognition systems that use either image acquisition devices, such as scanners or cameras in the case of fingerprint, hand or iris recognition technologies, or sound or movement acquisition devices, such as microphones or platens in the case of voice recognition or signature recognition technologies, to collect the biometric patterns or characteristics [2].

The characteristics of the acquired samples considered the most distinctive between users and the most stable for each user are extracted and encoded into a biometric reference or template that is a mathematical representation of a person's biometric feature. These templates are stored in a database or on a smart card or other token. Then that template is used for comparison when recognition is warranted. Before an individual's identity can be verified via a biometric, a biometric template or model must first be created. This stored template serves as the template data against which subsequent samples/templates provided at time of verification are compared.

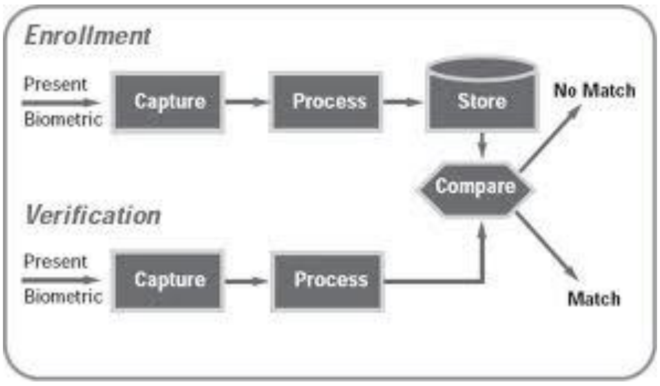

Fig.1. Generic biometric processes

For some technologies, a number of templates or images are typically captured during enrollment in order to create a truly representative template via an averaging or best image candidate selection process. The template is then referenced against an identifier in order to recall it for comparison with a live sample at the transaction or entry point. The positive ID verification/identification of the subject during the enrollment procedure and quality of the resultant template or reference are critical factors in the overall success of a biometric application. The former refers to the corroborating identity documents, commonly referred to as breeder documents the user brings to the initial enrollment process [3].

II. BIOMETRIC PERFORMANCE MEASURES

The performance of a biometric system is measured in certain standard terms. These are main three types of standard terms given below-

A. False Rejection Rate

FRR is the ratio of the number authorized users rejected by the biometric system to the total number of attempts made**.** False Rejection Rate has known as type 1 error, when a legitimate user is rejected because the system is not found that the current biometric data of the user similar to the biometric data in the templates that are stored in the database. Now since there is no zero error in a system that is in the real world, we calculate the FRR using a simple math equation:

$$FRR(\lambda) = \frac{\text{Number of False Rejection}}{\text{Total Number of Atempts}}$$

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B. *False Acceptance Rate*

FAR is the ratio of the number of unauthorized users accepted by the biometric system to the total of identification attempts to be made**.** This is also known as type 2 error, False Acceptance Rate is when an imposter is accepted as a legitimate user, This happens when the system find that the biometric data is similar to the template of a legitimate user. FAR is calculated by

$$FAR(\lambda) = \frac{\text{Number of False Attempts}}{\text{Total Number of Atempts}}$$

Where (λ) = Security Level

C. *Equal Error Rate*

Equal error rate is a point where FRR and FAR are same. The ERR is an indicator on how accurate the device is, the lower the ERR is the better the system.

Now if we have a score of the FAR & FRR we can create a graph that indicates the dependence of the FAR & FRR on the threshold value. The following is graph is an example:

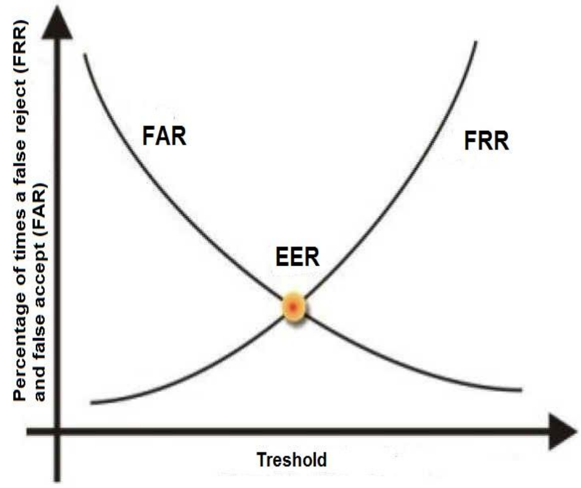

Fig. 2 Equal error rate

As we can see the curves of FAR and FRR cross at a point where FAR and FRR are equal, this obtained value is called Equal Error Rate or the Crossover Accuracy. If we have two devices with the equal error rates of 1% and 15% then more accurate device having the ERR of 1% . Most manufactures often publish the best achieved rates and not all manufactures use the same algorithms for calculating the rates.

III. COMMONLY USED BIOMETRIC TECHNOLOGIES

Biometrics is an effective personal identifier because the characteristics measured are distinct to each human also biometrics is tightly bound to an individual, they are more reliable, cannot be stolen, and are unable to be lost, forgotten, or otherwise compromised. The physical characteristics of a person like finger prints, hand geometry, face, voice and iris etc. are known as biometrics. Each biometric trait has its strengths and weaknesses. The suitable biometric can be selected depending upon the application in various computer based security systems. The important features of the various biometrics are discussed briefly in this section [4].

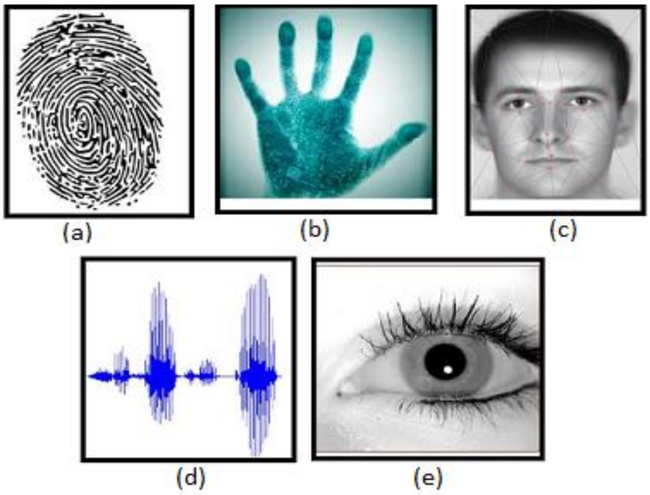

Fig. 3. Biometrics:
a) Fingerprint (b) Hand Geometry (c) Face (d) Voice
(e) Iris

A. *Finger Prints Recognition*

The finger prints of a person have been used as person identification from long time. A finger print is the pattern of rids and valley on the surface of a fingertip. The finger prints of the identical twins are different. It is affordable to scan the finger prints of a person and can be used in computer for number of applications. This fingerprint recognition system is becoming affordable in a large number of applications like banking, Passport etc. Fig.3(a) shows a sample finger print image of a person[5].

V. A. Sujan et.al [6] uses a segmented Fourier–Mellin transform to preprocess and using a HAusdorff–Voronoi NETwork (HAVNET), an artificial neural network designed for two-dimensional binary pattern recognition. HAVNET neural network improved recognition accuracy about 95%.

Dingrui Wan et.al [7] proposes a polynomial model to approximate the density map of fingerprints and used the model's parameters as a novel kind of feature for fingerprint representation. A decision-level fusion scheme is further used to combine the density map matching with conventional minutiae-based matching which gives better performance than using single minutiae-based matching

R. Kumar et.al [8] has been presented a system using multi-dimensional artificial neural network (MDANN) which takes in the two-dimensional minutiae image matrix as an input and a target output. The trained network can be used for the purpose of matching the fingerprints from the database giving 97.37% recognition rate.

Jucheng Yang et.al [9] proposes a scheme, based on the effective preprocessing with the STFT analysis, the extraction of local and global invariant moment features and the powerful SVM classification. Equal Error Rate (EER) is achieved about 2.38 %, which is better than Zernike moments based methods, geometry moments based, and the minutiae based methods.

B. *Hand Geometry Recognition*

The hand geometry recognition systems are based on a number of various measurements taken from the human hand, including its size and shape of palm, length and width of the fingers. This method is very simple and easy to use. As there is no effect of environment factors such as dry weather or dry skin, this does not appear to have negative effects on the authentication accuracy. Also hand geometry information may not be invariant during the growth period of the children [10]. The hand geometry is scanned as shown in fig. 3(b) and used for identification and recognition of a person.

J. J. Fuertes et.al [11] presents biometric identification-verification system using Support Vector Machines (SVMs) as feature extraction based on the fingers-widths and palm-print features. The combination of geometrical and palm-print data is used for feature calculation. Experiments have been performed on total 1440 samples from 144 users, 10 samples per user. Total 99.77% of recognition rate and a 0.0032% of equal error rate (EER) is reported.

Aythami M. et.al [12] proposes a novel contactless biometric system for multisampling hand recognition By including a novel acquisition device for contactless hand recognition and a study about the multi-sample acquisition as a way to improve the performance. Popular features extraction methods for hand geometry and palmprint are studied and experiments have been performed on a database of 100 people with more than 2000 hand. The results suggest how a multi-sample approach outperforms the traditional single sample approach with improvements around 47% and EER of 0.21%.

Nidhi Saxena et.al [13] presents an algorithm for recognizing the individuals using their hands automatically and a new thresholding algorithm for separating the hand from the background image consisting the lengths and widths of fingers and the width of a palm. In this method six different distance functions are tested and compared among them S1 gives the best results in both identification and verification. Matching algorithm compares and test eight different functions. In identification and verification processes, the weighted-combination of distance-IV and correlation functions yields the best performance. The identification rate for this algorithm is 97.44% and verification rate is 98.72 % giving the least error.

Chih-Lung Lin et.al [14] utilizes the vein patterns in the hand as a biometric. This is done by obtaining the vein pattern from the thermal image of the palm. Using the heat conduction law several features can be extracted from each feature point of the vein patters. The false acceptance rate (FAR) upto 3.5% while the false rejection rate (FRR) upto 1.5% is obtained.

David Zhang et.al [15] proposes a palmprint recognition method based on the eigenpalm technology. They obtained the Eigen vectors of the training set by transforming the original palmprints to a set of features. Also Euclidian distance classifier is used after extracting the Eigen vectors from a new palmprint for recognition. This system has FRR of about 1% and an FAR of around 0.03% on a set of 200 people. Bimodal systems, a combination of two biometrics using hand geometry and palmprints has been realized as an effective method to improve the performance of systems using hand geometry alone.

Kumar et.al [16] presents a bimodal biometric system using fusion of shape and texture of the hand. using discrete cosine transform palmprint authentication is done. A score level fusion of hand shape features and palmprints is done using product rule. Using either of hand shape geometry or palmprints alone produce high FRR and FAR but when the combination to form a bimodal system, it is considerably reduced. On a database of 100 users the FRR is found to be 0.6% and the FAR is found to be 0.43%.

C Chandra Sekhar et.al [17] has proposed a method to use hand contour as a feature vector for hand geometry. The aim of this hand based biometric system is to capture the uniqueness of the shape of an individual‘s hand. In this paper they explore traits like the shape of the hand contour and palm print texture as potential biometric verifiers. The novelty of this approach is the implicit capturing of the individual features in a single entity of hand contour. The sequence information of the contour is then fed to a hidden Markov model classifier. For palm print the feature vector used for classification is the texture energy measure. Texture provides a high-order description of the local image content. The texture analysis is based on the well documented Laws convolution masks. Linear and Gaussian kernel support vector machines are employed as classifiers. This scheme is viable for human authentication.

Raymond Veldhuis et.al [18] has been presented comparison of the performance of hand geometry recognition based on high-level features and on low-level features. A new method for hand-geometry verification is given, based on a model of the contour of the hand. By using a combination of principal component and linear discriminator analysis the dimensionality of the feature vector is reduced. An equal-error rate of 4% was measured in an evaluation experiment based on a data set containing a total of 850 hand contours of 51 peoples.

Vit Niennattrakul et.al [19] has proposed a hand geometry verification system using time series conversion techniques and dynamic time warping distance measurement with Sakoe-Chiba band. This system demonstrates many advantages, especially ease of implementation and small storage space requirement using time series representation. In this paper, they proposed a novel hand geometry verification system that exploits dynamic time warping distance measure and the R-K band learning method to further improve the system performance. In the system, two time series conversion techniques are applied, i.e., the centroid-based conversion technique and the angle-based technique. This experiment reveals that the centroid-based technique generally outperforms the angle-based technique by achieving lower EER and higher TSR.

J. M. Guo et.al [20] presents infrared illumination device employing to improve the usability of this hand recognition system, where users can place their hands freely in front of the camera without any pegs or templates and the system can be used in a normal environment without against dark background. The database is composed of 1600 images from 20 users, Correct Identification Rate (CIR) of 98.75% is obtained for identification and average False Accept Rate (FAR) is of 1.15%.

Vivek Kanhangad et.al [22] has proposed a new biometrics verification method by combining 2D and 3D hand geometry features. The proposed system utilizes a laser based 3D digitizer to acquire registered intensity and range images of the presented hands in a completely contact-free manner, without using any hand position restricting mechanism. Two new representations that characterize the local features on the finger surface are extracted from the acquired range images and are matched using the proposed matching metrics. This approach is evaluated on a database of 177 users, with 10 hand images for each user acquired in two sessions. The experimental results suggest that the 3D hand geometry features have significant discriminatory information to reliably authenticate individuals.

Ahmed Mostayed et.al [23] has proposed an authentication scheme from hand images which verifies with entire hand shape instead of dealing with hand measurements. Using radon transform, Peg free and position invariant features are calculated. Using a document scanner low resolution hand images captured are then processed to extract feature vectors. On a data set of 136 images the proposed scheme is tested with simple Euclidian norm based match score. The method gave an Equal Error Rate (EER) of 5.1%.

M. A. Sentosa et.al [25] demonstrated by using chain code and dynamic time wrapping method for hand geometry verification achieving success rate about 84% with FNMR (false non match rate) = 7.98% and FMR (false match rate) =7.92% for threshold value 206. Success rate is of the system is increases with increasing the number of training sample in database.

P. Rathi et.al [26] proposes a feature extraction system using hand contour matching and obtained by using Euclidian distance from starting reference point and then tip and valley point of finger is calculated. For that data is collected by capturing six images of 50 users. Three images respectively from left and right hand is captured in three different angles (90^0, 180^0, -180^0 angles). Reduction of features and integration of new features used to improve performance. Efficiency is improved by making multimodal biometric system.

Y. Bulatov et.al [27] has given a geometric classifier utilized in hand recognition. A document scanner is used to collect hand data in the proposed system where position of hand is not defined to place on the scanner. A total of 30 different features are obtained from a hand. For each individual 3 to 5 data images are used as the training set. For each of these training sets in the 30 dimensional feature space a bounding box is found. The distance of the query image to these bounding boxes are used as the measure of similarity. The threshold is determined by experimentation on the database.

C. Face Recognition

The face is the commonly used biometric characteristics for person recognition. The most popular approaches to face recognition are based on shape of facial attributes, such as eyes, eyebrows, nose, lips, chin and the relationships of these attributes. All these attributes of the face image are shown in fig. 3(c). As this technique involves many facial elements; these systems have difficulty in matching face images [28]. The face recognition systems which are used currently imposes some of restrictions on how facial images are obtained. This face recognition system automatically detects the correct face image and is able to recognize the person.

Wei Shen et.al [29] detailed a graph-based model named constrained message passing model for face identification. Training data set it is showed that system is comparable to the state-of-the-art methods using Labeled Faces in the Wild (LFW). Accuracy is obtained upto 84.50%.

V. H. Gaidhane et.al [30] experiments for the database of large variation in pose and illumination and shows the effectiveness for feature extraction and classification. The feasibility of the propose approach is demonstrated on three face databases, i.e., the ORL database, the Yale database Band the FERET database. In comparison with other methods performance is better also time taken for face recognition is less. Recognition rate achieved is 97.50% which is larger than other methods

L. A. Cament et.al [31] presents two new methods for face identification. The first one combines entropy-like weighted Gabor features with the local normalization of Gabor features. The second one fuses the entropy-like weighted Gabor features at the score level with the local Gabor binary pattern (LGBP) and the local Gabor XOR pattern (LGXP). Database of FERET, AR, and FRGC2.0 are tested and compared with previously reported methods. For pose variation the improvement in face recognition increased from 80.3% to 96.3%, i.e. 6% increase that could be due to the entropy-like weights on the Gabor jets

D. Voice Recognition

The voice recognition systems have been currently used in various applications. Voice is a combination of physical and behavioral biometrics. The fig. 3(d) shows a sample speech signal. The features of person voice are based on the vocal tracts, mouth, nasal activities and lips movement that are used synthesis of sound. These physical characteristics of human speech are invariant for individuals. The behavioral part of the speech of person affected with age, medical conditions, and emotional state[32].

Hossein Ghaffari Nik et.al [33] implements an effective method based on cross correlation of Mel Frequency Cepstral Coefficients (MFCC). Demonstration gives high accuracy for recognition of three words in a voice controlled system. The algorithm is tested for a total of 100 times, where each command was spoken 25 times and for the last 25 times noise and other words were used to check “No Selection” features of the system and tests resulted in 99% accuracy.

Everthon Silva Fonseca et.al [34] implements an adequate larynx pathology classifier to identify nodules in vocal folds based on Daubechies’ discrete wavelet transform (DWT-db), linear prediction coefficients (LPC), and least squares support vector machines (LS-SVM) giving 90% of classification accuracy and has a low order of computational complexity in relation to the speech signal’s length

Jian-Da Wu et.al [35] proposes a system for combination of feature extraction using continuous wavelet technique and voice classification using artificial neural network. In order to verify the effect of the proposed system for classification, a conventional back-propagation neural network (BPNN) and generalized regression neural network (GRNN) were used and compared in the experimental investigation. The identification rate 92% for using BPNN and 97% for using GRNN is achieved.

Sasan Adibi [36] implements very fast and efficient featured system having a high precision for the voice authentication mechanism, for that users voice harmonic information collected and for authentication of a speaker, various data manipulations are performed such as amplitude equalization, frequency scaling. At the time of authentication various voice collisions may be possible which depends on the sensitivity of the microphone, number of participating people, level of background noise, etc. The outcome of this voice authentication results a better than 96% accuracy of correctly identifying and authenticating the legitimate user

E. Iris Recognition

The iris is biological feature of a human. It is a unique structure of human which remains stable over a person lifetime. The iris is the annular region of the eye. Every individual has two irises which can be treated as separate unique identifier. A sample human eye image is given in fig. 3(e).The iris information can be collected by iris image. The accuracy of iris based recognition system is promising. Each iris is believed to be distinctive and even the irises of identical twins are also different [37]. The iris recognition system has become more users friendly and cost effective. The iris have a very low false accept rate as compared to other biometrics like finger print, face, hand geometry and voice.

Chia-Te Chou et.al [38] proposes a non-orthogonal view iris recognition system comprising a new iris imaging module, an iris segmentation module, an iris feature extraction module and a classification module. A dual-charge-coupled device camera was developed to capture four-spectral (red, green, blue, and near infrared) iris images which contain useful information for simplifying the iris segmentation task. The equal error rate is only 0.04% when recognizing iris images acquired at different off-axis angles within ±30°.

W. Dong et.al [39] proposes a personalized iris matching strategy using a class-specific weight map learned from the training images. Extensive and comprehensive experimental results have been clearly demonstrated that proposed strategy is effective for iris matching and greatly improves the performance of iris recognition systems. For every iris class, from 19 or 20 images select 10 selected as the training set to compute the weight map and the others as the testing set. From experiments it has been showed that the algorithm achieves FRR nearly equal to 0.03 when FAR =10^4, and if it is coordinated with the personalized weight map, then FRR will decrease to 0.01.

Fadi N. Sibai et.al [40] presents a simple methodology for pre-processing iris images and the design and training of a feed forward artificial neural network for iris recognition. Three different iris image data partitioning techniques and two data codings are proposed and explored. Brain-Maker simulations reveal that recognition accuracies as high as 93.33% can be reached despite our testing of similar irises of the same color.

IV. WHY HAND GEOMETRY?

Each biometrics has its advantages and disadvantages, and accordingly each biometric is used for a particular identification (authentication) application. Suitability of a particular biometric to a specific application depends upon various factors [41]; among them most significant factor is that the user acceptability. For many access control applications, like immigration, border control and dormitory meal plan access, very distinctive biometrics, e.g., fingerprint and iris, may not be acceptable for the sake of protecting an individual's privacy. In this type of situations, it is desirable that the given biometric indicator be only distinctive enough for verification but not for identification.

Hand geometry-based authentication for various other reasons is also very effective. People with disabilities could be easily engineered because almost all of the working population has hands also for exception processing [13]. Due to both the simplicity for scanning of the hand and due to a relatively simple method of sensing hand geometry measurements are easily collectible. In fingerprint imaging systems good frictional skin is required and by iris or retina-based identification systems a special illumination setup is needed, but hand geometry is ideally suited for integration with other biometrics, in particular, fingerprints. For instance, an identification/verification system may use fingerprints for (infrequent) identification and use hand geometry for (frequent) verification [42].

V. EVOLUTION OF HAND GEOMETRY

Hand Geometry, as the name suggests, refers to the geometric structure of the hand. This includes width of the palm, thickness of the palm, width of the fingers at various locations, length of the fingers, etc. According to the population these metrics do not vary significantly, they can however be used to verify the identity of an individual. Hand geometry measurement is non-intrusive and the verification involves a simple processing of the resulting features. As in palmprint verification methods this method does not involve extraction of detailed features of the hand (for example, wrinkles on the skin). Hand geometry-based verification systems are old techniques not recent and have been available since the early 1970s in some research. Authentication of identity of an individual based on a set of hand geometry features was an important research problem because it is well known that the individual hand features themselves are not very descriptive [43].

VI. ADVANTAGES OF HAND GEOMETRY BIOMETRICS

- Hand Geometry is Simple and relatively easy to use and inexpensive.
- Human hand contains enough anatomical characteristics to provide a mechanism for personal identification [44].
- Requirement of memory space is relatively less
- Hand geometry data is easier to collect, does not need a good frictional skin is required by imaging systems, and also special lighting is not required.
- Environmental factors are not an issue, such as, dry weather that causes the drying of the skin.
- Usually considered less intrusive than fingerprints, retinal, etc

VII. DRAWBACKS OF HAND GEOMETRY BIOMETRICS

- Human hand is not considered unique enough to provide mechanism for complete personal identification.
- Hand geometry is time sensitive and the shape of the hand can be changed during illness, aging or weight changing.
- Hand Geometry system is relatively costly than other

biometric systems.

- Used only where medium security is required.

VIII. CONCLUSION

The Biometric recognition systems uses the physical characteristics of a person for the automatic recognition systems. The biometric recognition systems have been proved to be accurate and very effective in various applications. Among all biometric systems hand-geometry based verification system can be used for access control in low-medium security zones and can also be combined with other forms of biometrics like finger print to increase the confidence levels in very high security zones. Some researchers and designers of commercial biometric systems consider hand shape to have a medium to high discrimination power. On the other hand, the authors of some recent research systems have shown high verification and identification rates which are comparable to fingerprint based systems. Only in the presence of a person the biometric features can be easily acquired and measured for the processing. Researchers in the field of biometrics found that human hand, especially human palm, contains some characteristics that can be used for personal identification. Thickness of the palm area and width, thickness and length of the fingers, etc. are main characteristics which can be considered for identification.

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