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Optimized Hand Geometry-Based Biometric Recognition System

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Abstract— In an era characterized by digital interactions and security needs, biometric systems, especially hand geometry-based recognition, offer an advantageous solution. Biometric identification through hand geometry is ideal for low-security applications due to its non-invasive nature and user-friendly features. This research discusses personal identification leveraging hand geometry features, notably without the use of pegs. Such features encompass finger length and width, palm dimensions, deviations, and angles. Image capturing was conducted without pegs. The study contrasts the use of 12 versus 21 hand geometry features. Identification was achieved using the Euclidean distance measure. The outcomes were validated on both a local and a standard database.

Keywords- Hand geometry, Biometric, Features, Recognition, Identification and Gaussian Mixture.

I. INTRODUCTION

In recent times, hand geometry-based personal identification systems have garnered significant attention from researchers due to their applicability in various scenarios. These systems determine an individual's identity through measurements of the human hand, encompassing its overall shape, palm size, and the dimensions of the fingers. One of the system's advantages is its resilience to environmental variables like dry weather or skin conditions, ensuring consistent recognition accuracy [1]. Obtaining hand images is straightforward, requiring basic tools like a webcam or digital camera, unlike other biometrics which may necessitate specialized and often costly scanners [2]. While capturing precise dimensions might sometimes necessitate pegs during scanning, the paper introduces a novel approach that forgoes this requirement. Hand geometry biometrics also boasts high user acceptability since it doesn't delve into intricate personal details. Moreover, the hand's features remain relatively stable post a certain age, and its template size is markedly smaller compared to other biometric systems[3]. This paper unveils a fresh perspective on hand recognition, emphasizing image acquisition without the need for pegs.

In the evolving landscape of digitization and interconnectedness, there emerges a critical need for secure and reliable identification and authentication systems. The demands of this age prioritize systems that can authenticate and identify individuals with precision, ease, and efficiency[4]. Recognition based on an individual's unique physiological and behavioral features has quickly become a preferred method thanks to the fast development of biometrics as a solution.

Hand geometry-based biometric identification stands out as a potentially useful and less invasive method among the several biometric modalities already in use, which include fingerprint, face, iris, and voice recognition[5]. Each person's physical characteristics may be deduced from the form, size, and arrangement of their hands and fingers. The shape of the hand has attracted researchers interested in biometric identification because of its accessibility, universality, and proven effectiveness in a variety of use cases.

However, hand geometry-based systems have yet to reach their full potential. While some current systems have shown promise, many problems still need to be solved before they can be considered fully reliable. This study focuses on improving biometric identification systems that use hand geometry by analyzing their performance under real-world conditions[6]. This presents will shed light on recent developments and provide a refined strategy for recognizing hand geometries. The various uses and advantages of such a system will also be presented. This will provide a framework for future research and advancements, in addition to underlining the relevance of hand geometry-based biometrics within the overall biometric domain.

II. LITERATURE SURVEY

Over the course of many decades, a wide variety of research investigations have contributed to the investigation of biometric hand identification systems that are based on hand geometry. This survey synthesizes the pivotal research, shedding light on the methodologies, findings, and implications each author has contributed to the field.

Author’s in [7] proposed an innovative technique for individual identification utilizing hand geometry attributes. Their study assessed 17 unique hand features, shedding light on the challenges associated with performance assessment in biometric verification systems. On a similar note, Sanchez-Reillo and colleagues [8] crafted a biometric system rooted in hand geometry, focusing on the distances and angles derived from hand images. Their method was able to extract a complete collection of 31 geometrical parameters, including as widths, heights, deviations, and angles between inter-finger locations. These elements were used to characterize the shape of the finger. They conducted research on several classification strategies and distance measures. Particularly noteworthy is the fact that GMM emerged as the best performer, with a success rate of 96%. Meanwhile, Author’s in [9] ventured into individual identification by leveraging both hand shape and texture-based attributes. Their approach measured characteristics such as the length and breadth of the palm as well as the fingers. To evaluate hand texture attributes, they employed wavelet transform preceded by Independent Component Analysis [10]. The results underscored ICA's superior performance in both identification and verification tasks.

Author’s in [11] developed a system for verifying individuals utilizing hand biometric attributes, employing three distinct techniques for feature extraction. The inaugural method leverages the hand's innate layout, eliminating the need for hand-pose training or a predetermined position during the registration phase [12]. The final technique centers around direct distance measurements.

Foundational Work in Hand Geometry: One of the pioneering figures in the realm of hand geometry-based systems, Conklin's research focused on introducing one of the first devices capable of recognizing individuals based on their hand's distinct characteristics.

Feature Extraction and Recognition Methods: This duo extensively studied feature extraction techniques from hand images [13]. Their methodology emphasized contour tracing, centroid calculation, and boundary point detection, laying a foundational approach for subsequent research in the field.

Integrative and Comparative Approaches: Their work is prominent in the domain of multi-modal biometric systems. They highlighted the efficiency of integrating fingerprint and hand geometry recognition, asserting an uptick in system reliability and accuracy [14]. Through comparative analysis, they underscored the unique advantages of hand geometry-based systems. Their results highlighted the non-intrusiveness and user-friendliness of hand geometry when juxtaposed with other biometric modalities.

Technological Innovations and Algorithmic Enhancements: With a focus on the technological progression in image acquisition, their research emphasized the positive implications of high-resolution imaging on hand geometry recognition accuracy[15]. Venturing into the realm of machine learning and deep learning, their research elucidated the benefits of employing Convolutional Neural Networks (CNN) for improved hand geometry recognition.

Addressing Challenges: This study brought attention to the potential threats of spoofing in hand geometry-based systems. The authors proposed several countermeasures, emphasizing the need for enhanced security protocols [16]. Tackling the challenge of scalability, their work explored efficient indexing methods and database pruning techniques to maintain accuracy while processing extensive databases.

Applications and Implementation: Their research elucidated the application of hand geometry-based systems in access control, particularly highlighting their efficiency in industrial settings [17]. Drawing from real-world scenarios, their study emphasized the feasibility and advantages of using hand geometry recognition in international airports and border control.

Looking Ahead: Their work delved into the prospects of hybrid systems, suggesting the potential of integrating hand geometry with vein pattern recognition for enhanced efficiency[18]. A notable contribution towards the standardization of hand geometry-based systems, their research advocated for universal data formats and interoperability standards.

In synthesizing this wealth of research, it becomes evident that hand geometry-based biometric recognition has undergone a transformation from its nascent stages to its current sophisticated form. The collective contributions of these researchers underpin the significance and evolving potential of this modality in biometric recognition.

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III. IMPLEMENTATION

To verify or identify a person, a Hand Geometry-Based Biometric Recognition System takes a picture of their hand and fingers, capturing the unique physical features of those parts of their body. The matching operations, as well as data collecting, preprocessing, feature extraction, database administration, and so on, are all included in this system. Within the enrollment module, features are extracted and subsequently saved to a database[19]. On the other hand, the authentication module will pull out features and compare them to those that have already been saved in the database. The comparison score is used to provide a result, which might be positive or negative depending on the outcome. As shown in Figure 1, the major procedures that are an important part of Hand Geometry Based identification include: a) Collection of Fingerprints; b) Image Refinement and Preprocessing; c) Derivation of Features; and d) Comparison and Verification.

Hand Scanner: High-resolution scanner or a camera equipped with infrared sensors for acquiring hand images. The infrared ensures capturing the depth and contour of the hand even in varying light conditions.

Computer System: A machine with adequate processing power, RAM, and storage to manage and process the hand geometry data.

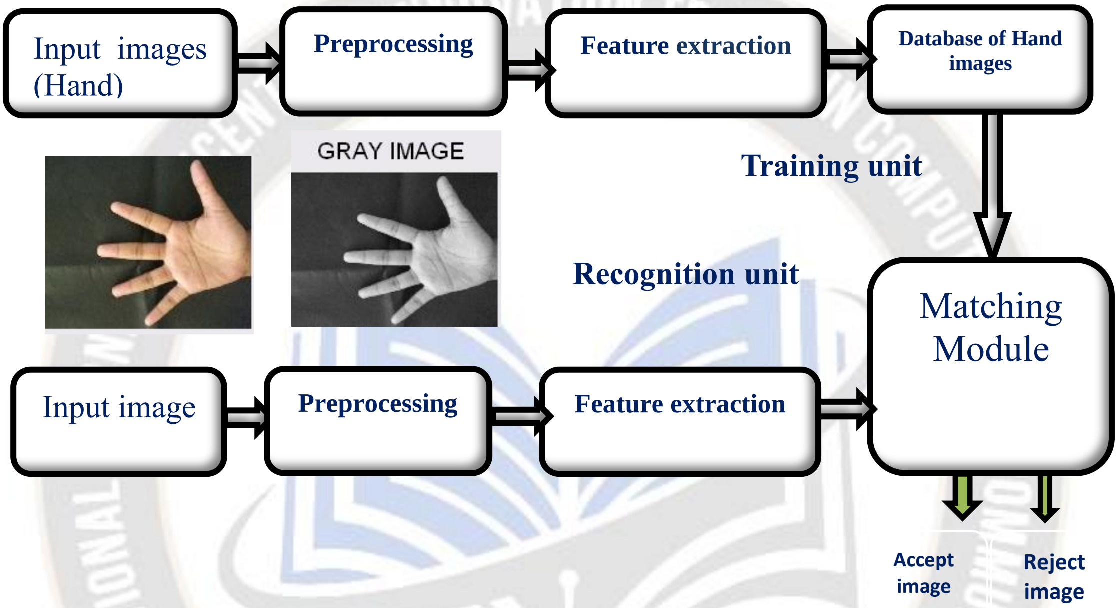


Figure.1: Block Diagram of Hand Geometry Recognition System

The subsequent section provides a detailed overview of the procedures undertaken for hand feature extraction within the enrollment module.

A. IMAGE ACQUISITION

The initial phase of a hand geometric system centers around image acquisition. This involves recording pictures with vision sensors such as color digital cameras, monochrome CCD cameras, color CCD cameras, video cameras, and scanners, amongst others, and then preserving them digitally[20]. The proposed method for the capture of images calls for the use of a digital camera in conjunction with a matte black background. Users are instructed to position one hand, with the backside making contact with the flat surface, fingers pointing upwards. Notably, the hand positioning is flexible due to the absence of pegs to set its placement[21]. Once positioned, the image is captured via the digital camera. The only directive for users is to ensure that their fingers remain separate and do not come into contact with each other.

Experiments were conducted on both the standard CASIA database and a proprietary local database. The CASIA Multi-Spectral Palmprint Image Database comprises 8-bit gray-level JPEG hand images. These images were captured using a CCD camera under varying illumination conditions. Notably, there aren't any pegs to limit the hand's posture or positioning.

We also established a local database[22]. This was compiled by collecting hand images from 200 unique individuals, with 5 images per person. These images were snapped using a NIKON COOLPIX S8 digital camera, boasting 7.1 megapixels and a 3x optical zoom. For our tests, we primarily sourced left-hand images of the participants, as depicted in Fig 2. The employed image resolution stands at 120 dpi.

Figure.2: Acquired Images

B. PREPROCESSING

Image preprocessing serves as the foundational stage, conditioning the image for subsequent analysis and utility. Essentially, the preprocessing module's objective is to ready the image for the feature extraction phase. The procedures encompassed within preprocessing include: Conversion from RGB to GRAY and the RGB image undergoes a transformation to yield a Gray image using the given method.

$$Intensity = 0.2989 * red + 0.5870 * green + 0.1140 * blue \quad (1)$$

C. BINARISATION

At this juncture, the gray-scale image undergoes a transformation into a binary representation where it adopts one of two possible values: 0 or 1. Here, '0' corresponds to the white color, while '1' signifies black. Figure.3, illustrates the progressive outcomes of the hand image preprocessing stages The conversion is steered by the following logic:

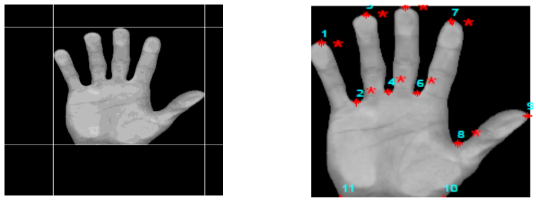
If the pixel value of the input picture at location (i, j) is lower than a predetermined threshold, the pixel value of the output image at location (i, j) will be set to 1.

On the other hand, if the pixel value at (i, j) of the input picture is equal to or higher than the threshold, then the pixel value at (i, j) of the output image will become 0.

In this notation, G(i,j) signifies the pixel's binary value post-binarization, whereas I(i,j) denotes its initial gray value.

$$if\ G(i,j) = \begin{cases} 1 & if\ I(i,j) > threshold \\ 0 & otherwise \end{cases} \quad (2)$$

(a) (b)



(c) (d)

Figure.3: illustrates the progressive outcomes of the hand image preprocessing stages: (a) Conversion from RGB to Gray-scale (b) The resultant Binarized image (c) Extraction of the image boundary (d) Designation of the minimum and maximum points on the hand image.

D. Feature Extraction

Algorithm for Boundary Detection of Hand Shape

Step 1: Begin by identifying the bottom right and bottom left points of the Hand image. To locate the bottom right point, commence searching from the bottom right pixel moving towards the bottom left pixel, guided by pixel values. To pinpoint the bottom left point, the search starts from the bottom left pixel towards the bottom right, also dictated by pixel values. Once both points are identified, the process halts and they're marked as point 12.

Step 2: Boundary tracing begins from point 12. The algorithm acknowledges eight directional references ranging from 0 to 7.

Step 3: Set the variable "dir" to 7.

Step 4: Explore the immediate 3x3 neighborhood of the current pixel in an anti-clockwise fashion. Initiate this exploration based on the position:

{(dir+7) mod8} for even values of dir

{(dir+6) mod8} for odd values of dir

The next element on the boundary corresponds to the first pixel located with a value matching the current pixel. Subsequently, modify the value of dir.

Step 5: If the penultimate border element (n-1) equals 0 and the current boundary element equates to the second boundary component, then the procedure may be finished. If not, go to the second step.

E. Recognizing hand geometry using 12 geometry features

The feature vector in this system is derived by taking the distance that exists between the points that are considered to be the greatest and the lowest. As shown in Figure 4, there are six minimum points, six maximum points, and a total of twelve distance parameters as a consequence of these two types of points. The number of elements that make up the feature vector is 12.

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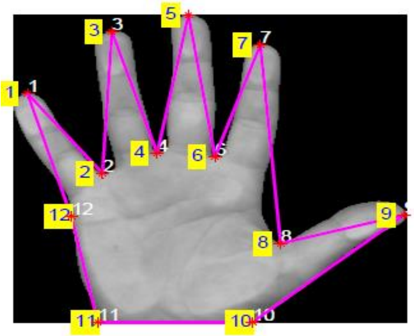

Figure.4:Handgeometry 12 features

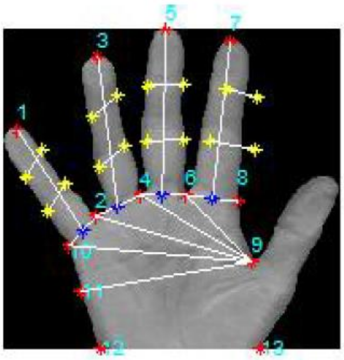

Figure.5: Handgeometry 21 features

F. HandgeometryRecognitionusing21Geometry Features

In this method, the length of each finger is measured only once, while each finger's breadth is measured three times. In addition, the breadth of the palm and four distances are measured. These distances are measured from the valley point of the thumb to the valley points of the index, ring, middle, and little fingers, respectively. We acquire a total of sixteen characteristics from the four fingers when they are combined; they include one measurement for each finger's length and three measurements for each finger's breadth. As shown in Figure 5, there are a total of 21 traits, the most notable of which are the breadth of the palm and the four distances that separate the valley point of the thumb from the valley points of the other fingers.

The system extracts a total of 21 features, described as follows:

Finger Length: The length of the finger may be measured by measuring the distance from the tip of the finger to the baseline's middle point. This gives the finger's overall length. One length measurement is taken for each individual finger on the hand. As a result, four characteristics may be inferred from finger lengths.

Finger Width: Measurements Taken at Three Different Points on the Finger The width of a finger is measured at three different points on the finger: At the position that is exactly in the middle of the finger's length, at the point that is exactly one-third of the finger's length, and between the two smallest points on the finger, as shown in figure 5.

Palm Width: Represented by the distance from point 9 to 11, as illustrated in Fig. 5.

Distance D1 (9 to 10): This is a measurement of the distance between the valley point of the thumb and the valley point of the little finger.

Distance D2 (9 to 2): This captures the gap between the thumb's valley and the ring finger's valley point.

Distance D3 (9 to 4): This represents the interval between the thumb's valley point and the middle finger's valley point.

Distance D4 (9 to 6): The distance between the valley point of the thumb and the valley point of the index finger may be determined using this method.

The sum total of these metrics constitutes a complete collection of 21 characteristics that are provided by the system. The Hand Geometry-Based Biometric Recognition System is a one-of-a-kind method for authenticating users that is based on the physical characteristics of the hand. Proper implementation ensures accurate and secure user authentication, while continuous updates keep the system robust against potential challenges.

IV. RESULTS & DISCUSSION

Both a conventional database, known as the CASIA database, and our very own locally collected information were used in the evaluation of the efficacy of the approach that was presented. Several different standardized criteria are frequently used in the process of determining how effective a biometric system is. The following are some examples of them:

False Acceptance Rate, abbreviated as FAR, is the likelihood that the system would incorrectly authenticate an unlawful user. This rate is expressed as a percentage.

False Rejection Rate, sometimes referred to as FRR or False Rejection likelihood, is the likelihood that the system would mistakenly reject access to an authorized user. Other names for this statistic are FRR and False Rejection Probability.

The point at which the FAR and the FRR overlap is known as the Equal Error Rate (EER), and it is denoted by the letters "EER." It is a standard measure that is used to provide a single number in order to emphasize the performance of a biometric system. The objective of this measure is to highlight the performance of the system. When compared to higher EER

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levels, a system's improved performance is often indicated by lower EER levels.

False accept rate (FAR)

In this section we get a mention of the False Acceptance Rate (FAR), also written as FAR. The FAR may be calculated by dividing the number of legitimate users enrolled in the system by the number of unauthorized users who were falsely verified by the system. The FAR is determined on the basis of this ratio. It's a way to quantify how likely it is that a biometric system may mistakenly verify an imposter as a genuine user. Because of the higher possibility of providing access to imposters, a system with a bigger FAR is likely to have a lower degree of security. This is because there is a higher likelihood of gaining access to fakes via this approach.

$$FAR = \frac{\text{Number of persons accepted incorrectly}}{\text{Total number of persons in database}} \;..(2)$$

$$FAR = \frac{\text{FP}}{\text{FP + TN}} \quad \dots\dots\dots\dots..(3)$$

Here we break down the False Rejection Rate (FRR), often known as the percentage of false negatives in a given sample. If we divide the total number of users by the number of authorized users whose requests were incorrectly denied, we get the false-rejection rate (FRR). The quotient so obtained is then divided by the total number of users in the database. The first step in determining the FRR is to multiply this ratio by 100. It is a sign that there is a potential for the biometric system to incorrectly refuse access to a user who is authorized to make use of it. A larger FRR might be annoying for users, since it increases the likelihood that real persons will run against access restrictions more often.

$$FRR = \frac{\text{Number of persons rejected}}{\text{Total number of persons in database}} \dots (4)$$

$$FRR = \frac{\text{FN}}{\text{FN + TP}} \dots\dots.(5)$$

Genuine Acceptance Rate (GAR): The GAR, which is also sometimes called the True Acceptance Rate (TAR). It's a measure of how often a biometric system correctly authenticates authorized individuals.

The formula for GAR is: GAR = 1-FRR………..(6)

FRR is the False Rejection Rate. The GAR indicates the percentage of times genuine users are correctly authenticated by the system. A higher GAR means the system has a higher accuracy in recognizing and accepting genuine users.

The GAR is crucial as it indicates the precision of a biometric system. By contrasting the GAR values of two distinct systems, we can evaluate their performance. The system with a superior GAR score is deemed to be the more reliable one.

Equal Error Rate(EER): On the graph that illustrates the difference between FAR and FRR, the EER is shown as the point at where the two curves meet. When comparing two different biometric systems, the EER is used since the threshold value affects both the false acceptance rate and the false denial rate. It is generally agreed that a system with a lower EER is the more dependable option.

For the purpose of demonstrating the reliability of a biometric system, performance metrics are often provided in the form of a variety of graphs or curves. The Receiver Operating Characteristics (ROC) curve is the one that is used most commonly for usage in biometric verification. This curve plots the FAR against the FRR at varying thresholds. When the FAR and FRR have equivalent values, the biometric system's performance can be described using the Equal Error Rate (EER), which corresponds to a specific point on the ROC curve. A lower EER signifies superior performance.

Figure 6 displays the results of a unimodal hand geometry identification system using a local database. The EER value for the system with 21 features is lower compared to the one with 12 hand geometry features. This indicates that the performance of the system with 21 features is superior to that of the 12-feature system. Figure 7 showcases the ROC curve (plotting FAR against GAR), presenting the outcomes for the unimodal hand geometry identification system based on the same local database.

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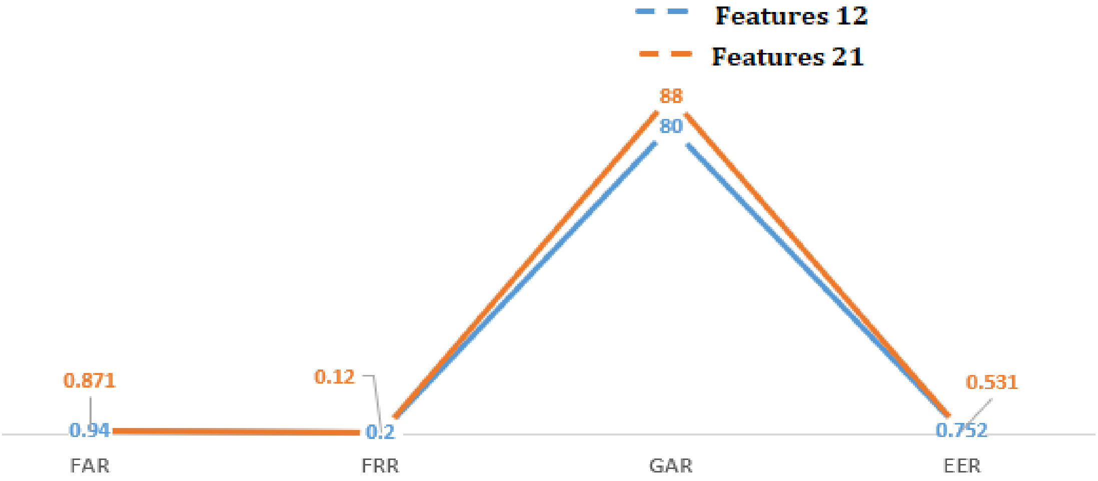

Figure.6: Analyzing Hand Geometry Recognition Systems for Local Databases

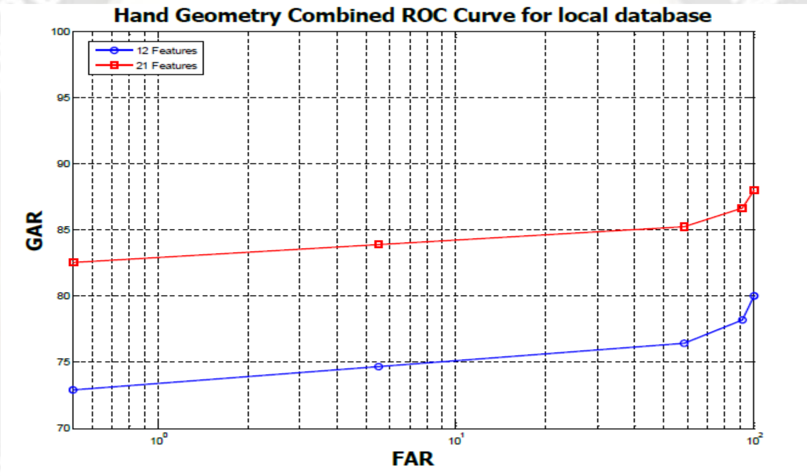

Figure.7: Unified ROC Curve Analysis for Hand Geometry in Local Databases

Figure 8 illustrates the outcomes of a unimodal hand geometry identification system using the Casia database. The system with 21 features has a lower EER value compared to the one with 12 hand geometry features. This suggests that the 21-feature system performs better than the system with 12 hand geometry features.

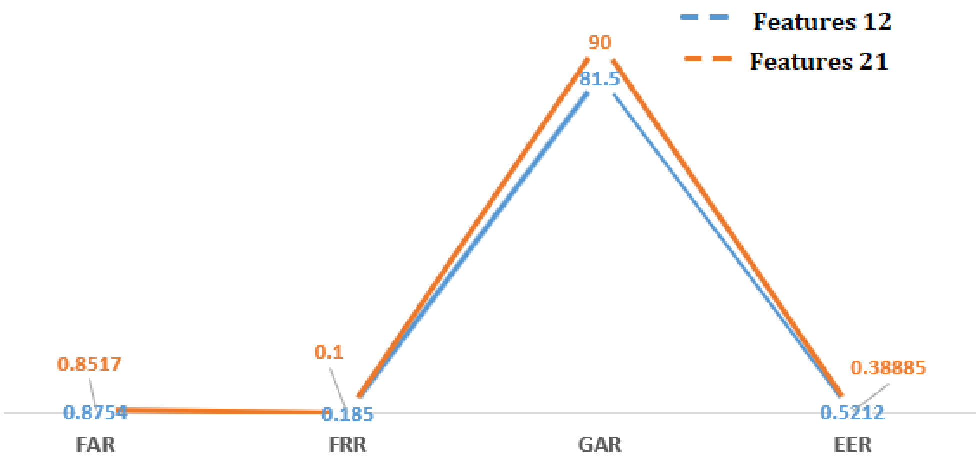

Figure.8: Analysis of Hand Geometry Identification Systems with the Help of the CASIA Database

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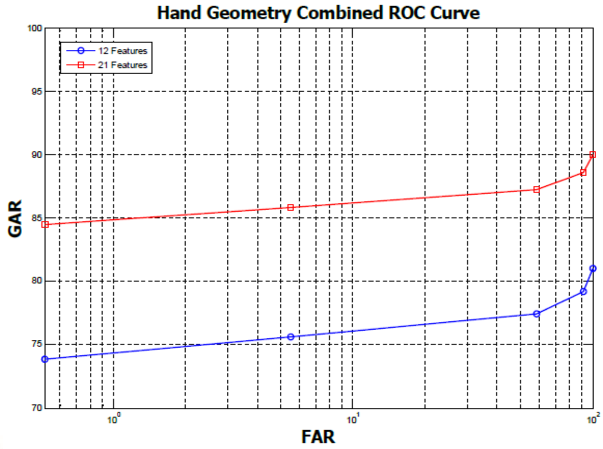

Figure.9: Analyzing Hand Geometry Using the CASIA Database as Part of an Integrated ROC Curve

Figure 9 shows the ROC curve (a plot of FAR vs GAR) for the Casia-based unimodal hand geometry detection system. A higher GAR value for the 21-feature system compared to the 12-feature system for hand geometry indicates that the 21-feature system performs better.

V. CONCLUSION

Rapid technological progress has prompted the development of more robust methods of authentication and identity. Biometric technologies have quickly become a frontrunner, with hand geometry-based identification providing a particularly attractive mix of use and safety. The purpose of this research was to improve the accuracy of the recognition process by delving deeply into the complexities of biometrics that are dependent on the geometry of the hand. This Hand Geometric Recognition method is able to identify a person based on the specific measurements of their hands, which may include the length, width, angles, and deviations of their hands. This system is widely used for both physical and virtual access control because of its versatility and user-friendliness. However, because to its less unique feature representation, the hand geometry approach has mostly been employed for low- to medium-security authentication jobs. In order to improve the accuracy and dependability of the system, it is possible to integrate the properties of the user's hand geometry with those obtained from other biometric modalities, such as palm prints and fingerprints.

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