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# Design of a Hybrid Metric for Fingerprint Image Matching: A Grediant, Aczil, and SourceAFIS Approach

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**Abstract**

One of the most popular biometric matchings is the fingerprint used for personal matching, verification, and authentication. Numerous fingerprint metrics have been developed to detect various types of fingerprint image distortions. The majority of these metrics are based on a single approach. It is feasible to match a specific person's fingerprint image by comparing images of the same person's fingerprint, which we will discuss in detail in this paper. In this work, we provide an alternative technique by interpolating the Aczel metric with gradient matching and Source Automated Fingerprint Matching System (SourceAFIS) algorithm. The Aczel metric demonstrates strong predictive capabilities in discerning relationships among intensity values within fingerprint images while gradient matching is used to gage the change in contrast and structure in images. SourceAFIS describes fingerprints using high-level abstractions called minutiae, creates edges, matches minutiae and edges, and scores pairings based on random feature likelihood. The combined method has been tested against powerful statistical approaches for image analysis such as gradient matching metric and SourceAFIS matching algorithm. Simulation results using four well-known FVC2000, FVC2002, FVC2004, and FVC2006 image databases prove the effectiveness of the proposed technique achieves better consequences than the current methods in matching fingerprint images.

**Keywords**: Fingerprint, Matching, SourceAFIS, Gradient, Aczel.

## 1. Introduction

An impression left by the grinding edges of a human finger is called a unique mark. The recuperation of halfway fingerprints from a wrongdoing scene is a critical strategy of legal science. Whenever a finger is damp or oily, it leaves a fingerprint on a surface like glass or metal. These distinctive features are crucial in the Matching and verification of individuals, as they provide a unique and reliable method of authentication in various settings such as law enforcement, border control, and access control systems. Although the fingerprint system is very significant as we mentioned here but still face some challenges, for instance, biometric performance, environmental influences, usability and acceptability, touch-to-touchless-based sensor interoperability, presentation attack detection, biometric template protection, and multi-biometrics [1]. A detailed examination of advancements in fingerprint Matching technology to counter spoofing attacks is the focus of Spoofing Challenges analysis [2]. Contact fingerprints, like live-scan and wet-inked fingerprints, involve the finger physically touching a sensor, while contact fingerprint images may have distinct ridges and valleys with strong contrast, the act of physically touching the fingerprint can lead to complications during acquisition. First, the fingerprints that are taken may be tainted by the latent fingerprints from previous individuals on the surface of the sensor. Also, fingerprints will exhibit var-

ying degrees of nonlinear distortion due to the differing pressure on the sensor surface during the capturing process. This will decrease the precision of the comparison. Furthermore, pathogens like coronaviruses have the potential to be transmitted through the sensor surface, creating pandemic risks such as COVID-19[3]. Additional hurdles in image matching technology result from the absence of comprehensive perceptual models for real-world images, supra threshold distortions, the complex relationship between distortions and images, images with various non-traditional distortions, and images with enhancements. Main objective of this work is not just to point out the constraints in our existing understanding of image quality, but also to stress the importance of further basic research in aligning perception [4]. Several studies focused on the approach of matching fingerprint images. Previous efforts have addressed many difficult aspects of fingerprint Matching in order to enable real-time functionality in the system. J Mader and T Lorünser show how to make fingerprint matching better by looking at small details with encrypted data. They use a method called Multiparty Computation (MPC) and use the SourceAFIS algorithm [5]. Y Zhang and colleagues suggested a method for matching fingerprints that includes liveness detection. The writers utilize Optimal Neighborhood Search Space (ONNS) to determine the correspondence between two fingerprint images, then calculate FLD score of the fingerprint image with the help of the revised Residual Network (Slim-ResCNN). In the end, logistic regression (LR) classifiers are used to analyze the score feature vector [6]. AFY Althabhawee suggests a fingerprint authentication model implementing a deep learning-based deep convolutional neural network (CNN or ConvNet). The suggested design includes 15 layers and is divided into two phases. The initial phase involves preparatory tasks like gathering fingerprint images, augmenting them, and pre-processing them, while the subsequent phase involves extracting and matching features [7]. J Priesnitz and colleagues present a summary of the latest advancements in touchless 2D fingerprint Matching throughout every step of the Matching process [8]. Wani et al introduced a fingerprint recognition system that relies on supervised deep learning [9]. The method proposed by DM Uliyan et al utilized Discriminative Restricted Boltzmann Machines to accurately distinguish fingerprints from fabricated materials for spoofing purposes [10]. J Priesnitz et al introduced a hands-free fingerprint Matching system for smartphones. The technique can automatically capture the four fingers on the inside of a hand and convert them into individual fingerprint images [11]. Anil K. Jain introduced the C2CL system, which includes a mobile app for capturing finger photos, preprocessing, and matching algorithms to address challenges in previous cross-matching techniques; the matching algorithm captures minutiae and texture representations [12]. This article discusses the Aczel method [13] with the following parts: Second part outlines the existence metrics; third part presents the proposed metric; while fourth part introduces the simulation results and discussion, and fifth part concludes with future work.

# 2. Matching Methods

## 2.1. Gradient Matching Metric (GMM):

A Liu et al [14] proposed the Gradient matching metric (GMM) to measure the variations in contrast and structure in images. GMM evaluates image quality effectively by taking into account changes in both brightness and contrast. Additionally, the GMM is structured to closely adhere to the masking effect and visibility thresh-

old, specifically addressing situations where both masked and masking signals are minimal more efficiently. The provided formula defines GMM:

$$g(x,y) = \frac{2g_x g_y + C4}{g_x^2 + g_y^2 + C4} \quad (1)$$

where $g_x$ and $g_y$ represent the gradient values for the middle pixel of image blocks x and y, with $C4$ serving as a small constant to prevent division by zero. The gradient matching between x and y, denoted as $g(x,y)$, falls within the range of [0, 1]. GMM is able to measure the relative loss of quality, particularly in the areas near the edges and within non-edged regions. The gradient value $g_x$ (also $g_y$) is determined by finding the highest weighted average:

$$g_x = \{max_{k=1,2,3,4} mean2(|x.M_k|)\} \quad (2)$$

$M_k$ represents the operator used to calculate the gradient value, with k ranging from 1 to 4, while $mean2(.)$ Refers to the mean value of the image. The suggested version of $g(x,y)$ can measure changes in both image contrast and image structure by utilizing the gradient value as a feature that encompasses both contrast and structure aspects. Firstly, let's take the example of $y = \gamma.x$ where $\gamma$ is a constant and $\gamma \neq 1$. In this case, $g_y = \gamma.g_x$. Consequently, $g_y$ and $g_x$ are not equal because $\gamma \neq 1$. This demonstrates that $g_x$ is a feature that varies in contrast. Ultimately, the impact of alterations in brightness and contrast is combined using an adaptable approach to determine the quality rating of the image. The highlighted feature of GMM is utilized in our proposed metric for establishing novel matching fingerprint images.

## 2.2. The Aczel Method:

The Aczel method can be used to the sake of fingerprint images to achieve the desired goal of matching. This technique provides more accurate analysis and manipulation of fingerprint images in biometric and forensic investigations through subjective probability and information theory. the Aczel approach can be utilized for fingerprint images by representing fingerprint-matching uncertainty as a subjective probability. the Aczel approach can be used to independently estimate the information content in the image due to their intrinsic properties. In this respect, high information content in some areas of the fingerprint image may indicate unique features useful for matching. the Aczel metric can help in fingerprint matching by integrating prior knowledge of fingerprint patterns and updating the likelihood of a match given what is observed in the fingerprint images to get a higher accuracy and reliability of fingerprint matching. Using the maximum of the Aczel principle is one of the methods that can guide the selection of probability distributions when modeling fingerprint data; it allows for maximizing the information content of the fingerprint features and reducing bias in the analysis. It is by this approach from Aczel that fingerprint matching can, much more soundly, be regarded as a means of updating one's beliefs and producing decisions, as such, allowing for a much more robust and systematic comparison concerning fingerprint images. The analyst can then make informed decisions based on a combination of prior knowledge in light of the observed evidence. Such applications of the Aczel approach to fingerprint images will lead to the creation of secure biometric authentication systems and robust forensic analysis tools. Quantifying uncertainty, maximizing information content, and using Bayesian inference can significantly enhance the reliability and accuracy of fingerprint matching. The inclusion of the Aczel approach in the fingerprint image examination provides a principled and structured methodology in the area of fingerprint matching, thereby increasing the accuracy,

reliability, and interpretability of the matching process [14]-[18]. Next is a subsection on how the Aczel metric is applied over the gradient matching metric and SourceAFIS to obtain the proposed metric, resulting in better matching robustness than existing metrics. The following formula gives the Aczel function:

$$A_i(x) = -\sum_{i=1}^{n} p^r(x_i)[p(x_i)] \quad (3)$$

[19], where $A_i$ represents the Aczel metric, $x$ is a discrete random variable $x = \{x_1, x_2, \dots\dots, x_n\}$ and $p(x_i)$ is a probability of event $x_i$, $p \in [0,1]$. This function integrated with the GMM and SourceAFIS to give the proposed metric

### 2.3. Source Automated Fingerprint Matching System

The SourceAFIS is considered one of the superior fingerprint image-matching algorithms used by many works such as [20], [22]. Almost 77 research papers on Google Scholar in the time range between 2020 and 2024 talk about SourceAFIS as a fingerprint matcher, but none of them use SourceAFIS in a hybrid metric like what we did in this work in our proposed metric. The SourceAFIS founded by Robert Važan [23] works with two different matching scenarios, 1:1 and 1:N. where 1:1 means that compare two fingerprint images as a test image and reference image while 1:N referees to compare fingerprint images as one reference image with the database images to find the matching. The mathematical syntax of the SourceAFIS represents the process of the algorithm for matching based on three steps: minutiae representation, similarity score calculation, and thresholding for match decision. Minutiae points can be represented as:

$$M = \{(x_i, y_i, \theta_i) \mid i = 1,2, \dots, n \quad (4)$$

where $M$ is the set of minutiae, $(x_i, y_i)$ are the coordinates of the $i^{th}$ minutia, and $\theta_i$ is its orientation. The similarity score $S$ between two fingerprint templates $M_p$ (probe) and $M_c$ (candidate) can be computed using a combination of distance and orientation:

$$S = \omega_d \cdot D(M_p, M_c) + \omega_o \cdot O(M_p, M_c) \quad (5)$$

Where $D(M_p, M_c)$ is the Euclidean distance metric between corresponding minutiae. $O(M_p, M_c)$ is the orientation similarity based on the angles of minutiae. $\omega_d$ and $\omega_o$ are weights that balance the contributions of distance and orientation to the overall score. A match decision can be expressed as:

$$\text{Match} = \begin{cases} True\ if\ S \geq T \\ False\ if\ S < T \end{cases} \quad (6)$$

where $T$ is a customizable threshold that determines the acceptance of a match.

## 3. Proposed Metric

To find a match of any two digital images, we have to gauge the matching test between them. During the acquisition of the images, the process faces several challenges as we discussed in the introduction section. To solve these problems, we need to enhance the performance of the well-known metrics by incorporating them with a related concept that has the ability to improve the rate of matching success. In our proposed metric the combination approach has achieved a superior result for the sake of matching. In this paper we combined the GMM metric with the Aczel approach and the inclusion of the SourceAFIS into proposed hybrid metric to give a more reliable matching metric. The basic idea of the proposed metric is to make all the components work simultaneously on the test image and reference image or on the test image and database images to give more reliable and accurate results. The main components of the hybrid metric are given by the equation below:

$$Sr(f1,f2) = \frac{S(f1,f2).A(f1,f2).(a+b)+e}{a.S(f1,f2).A(f1,f2)+b.A(f1,f2)+c.G(f1,f2)+e} \quad (7)$$

Where $Sr$ represent the proposed hybrid metric between the reference image $f1$ and test image $f2$. $A(f1,f2)$ refers to the Aczel metric that introduced in the 3.1 section.

The inclusion of SourceAFIS as an independent matching metric is the core of the proposed hybrid metric. $S(f1,f2)$ is indicated the SourceAFIS takes a two-dimensional of an image's spatial frequency and highlights regions of high spatial resolution. It then finds the absolute magnitude of the gradient at each point. The last component in the proposed equation is the GMM which is elaborated in section 2.1 above. The hybrid metric will integrate the three methods as shown:

$$H(x,y) = b \cdot A(f1,f2) + c \cdot G(f1,f2) + a \cdot S(f1,f2) \quad (8)$$

Let a = 0.3, b = 0.5, and c = 0.7 be weighting factors. Each set of these empirical and statistically validated values is derived from testing and, hence, comparison. We have carried out many experiments to determine the best weighting combination through fingerprint image comparison in various datasets and noise conditions. The SourceAFIS component (0.3) guarantees reliable uniqueness detection. The Aczel component (0.5) guarantees robustness to illumination changes. The Gradient Matching component (0.7) guarantees minutiae-based matching. Numerous experiments confirm that the best weight combination is achieved through noise image fingerprint recognition. To estimate the impact of parameter variations, we tested exceptional combinations of weight on FVC2000, FVC2002, FVC2004 and FVC2006 database. The results of the exams are given within the following table:

**Table 1. Fingerprint Verification Competition (FVC) Accuracy Comparison Across Different Parameter Sets (a, b, c) and Equal Weights**

| Parameter Set | FVC2000 Accuracy | FVC2002 Accuracy | FVC2004 Accuracy | FVC2006 Accuracy |
|---|---|---|---|---|
| (a=0.3, b=0.5, c=0.7) | 98.9% | 99.1% | 98.6% | 99.3% |
| (a=0.5, b=0.3, c=0.7) | 96.8% | 97.5% | 96.2% | 97.9% |
| (a=0.2, b=0.6, c=0.8) | 97.1% | 98.0% | 97.4% | 98.2% |
| Equal Weights | 94.5% | 95.1% | 94.0% | 95.8% |

The outcomes display that the proposed weights a=0.3, b=0.5, c=0.7 provide the very best accuracy throughout datasets. Putting more weight on Aczel beyond 0.3 accomplished worse because of the over dependence on probabilistic capabilities, while lowering the burden of SourceAFIS reduced overall performance in complicated cases.

The unique flavor of the proposed metric is the smart integration of the best features of the three methods which is leads to solve the limitation of the ScourceAFIS in case of ridges being combined into a single thick ridge.

# 4. Results and Discussion

We have implemented the proposed metrics on MATLAB2024a and tested their performance against other metrics as follows.

## 4.1. Fingerprint Images databases

In this experiment, we applied the metrics on the most common series of fingerprint image databases which are FVC 2000, FVC 2002, FVC 2004 and FVC2006 as shown in the figures below. In the Fig. 1 FVC2000 database consists of four different scenarios (DB1, DB2, DB3, and DB4) were utilized to evaluate the fingerprint techniques in this work. DB1 and DB2 are small-size. DB3 was a higher quality (large area). DB4 was generated by utilized the approach described in [24]. Each scenario was split into two categories: reference images include 10 images for each scenario, so the total number of reference images is 40 and an open training image consists of 8 images as impressions made available to participants for the algorithm, so the total test images are 80.

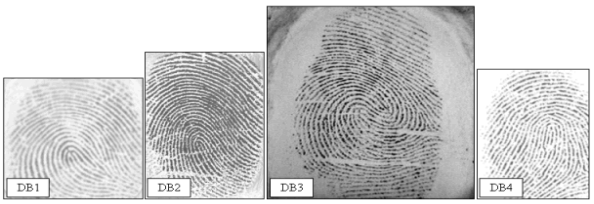


Fig. 1. FVC 2000

In the Fig. 2 FVC2002 is the Second International Competition for Fingerprint Verification database [25]. The full FVC2000 and FVC2002 databases are available in the DVD included in the handbook of fingerprint matching (2nd Edition) [26].

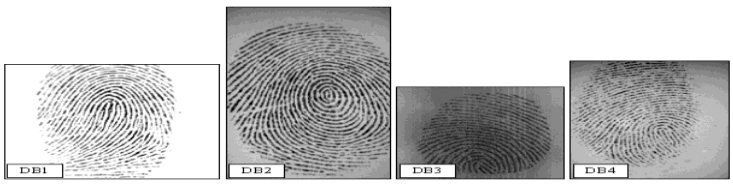


Fig. 2. FVC 2002

In the Fig 3. FVC2004 is the third fingerprint database has been utilized in this domain [27]. FVC2004 include three real and one synthetic from two categories (Open Category and Light Category). This database has 43 participants (29 industrial, 6 academics, and 8 independent developers) from different countries such as Russia, Korea, China, Poland, France, Lithuania, Ukraine, Canada, Germany, and Argentina. The four databases (DB1, DB2, DB3, and DB4) were obtained through various sensors/technologies: DB1 used the optical sensor "V300" from Cross-Match, DB2 used the optical sensor "U.are.U 4000" from Digital Persona, DB3 used the thermal sweeping sensor "FingerChip FCD4B14CB" from Atmel, and DB4 utilized synthetic fingerprint generation. FVC2004 databases are considerably harder than FVC2002 and FVC2000 databases because of the intentionally added disturbances.

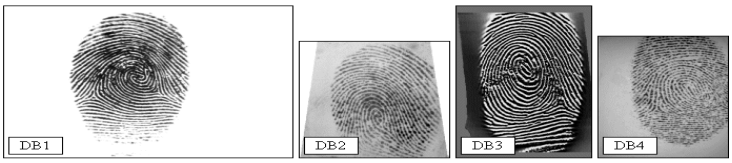

Fig. 3. FVC 2004

In the Fig. 4 FVC2006 [28] is last fingerprint database used in this work to evaluate the results of the fingerprint metrics. The FVC2006 competition focuses on the assessment of fingerprint verification software. For the purpose of adjusting the parameters of their algorithm's, registered participants were provided with a subset of fingerprint impressions acquired with various sensors. In addition to providing enrolled and matched executable files, the organizers provided information from their training set as well as an evaluation using the submitted executable files on a sequestered database. FVC2006 database also like FVC2004 included (three real and one synthetic) with two classifications and fifty-three participants (twenty-seven industrial, thirteen academics, and thirteen independent developers).

Fig. 4. FVC 2006

## 4.2. Evaluation Criteria

The effectiveness of the new hybrid metric has been compared to two other matching metrics: ScouceAFIS metric and gradient matching metric. The indication of success is the uncertainty in determining if an image is part of a database. The discrepancy is measured by the variance in matching results (using a specified metric) between the reference image and the database images, specifically looking at the top two matches. High confusion and low performance occur when there is minimal difference in matching between various fingerprint images in a metric as shown in the figure 5.

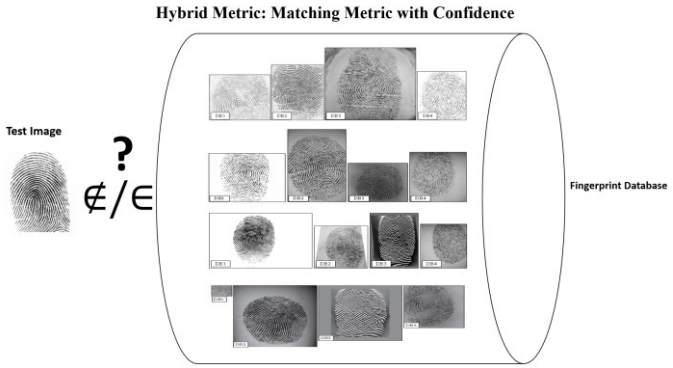

Fig. 5. A test fingerprint image is evaluated against a fingerprint database to determine its presence (∈) or absence (∉) in the dataset, based on the similarity score and confidence level.

To confirm the total performance of the proposed method, we recall the following major assessment criteria: false acceptance rate (FAR), false rejection rate (FRR), equal error rate (EER), and calculation time. These criteria ensure a comprehensive evaluation and cover each accuracy and efficiency component. The effects can be analyzed based on these metrics to determine the effectiveness of the proposed method. To calculate FAR, FRR, EER, and computation time, we will extract the necessary values and integrate the required calculations. The False Acceptance Rate (FAR) is the probability that an unauthorized user is falsely accepted by the system, expressed as

$$FAR = \frac{F_A}{F_A + F_R} \tag{9}$$

Where $F_A$ is the number of false acceptances and $F_R$ is the number of false rejections. The False Rejection Rate (FRR) is the probability of a legitimate user being falsely rejected, stated as

$$FRR = \frac{F_R}{F_A + F_R} \tag{10}$$

Equal Error Rate (EER) is the point at which FAR and FRR are equal and is a key performance metric of biometric systems. Computation time is the processing time to verify the user, which is quantified in milliseconds or seconds as shown in figure 6. The computation time is 0.0956 seconds, which is quite fast for real-time authentication; this is a good processing speed.

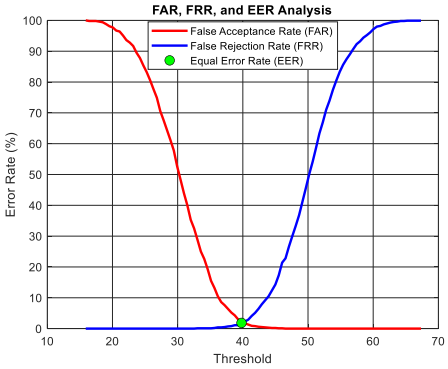


Fig. 6. The graph charts the FAR and FRR over a range of threshold values. The EER, marked by the green dot, is 2.80% at a threshold of 40.46, where FAR and FRR intersect.

## 4.3. Implementation of Matching

The result obtained from applying the hybrid proposed measure against the basic components of the hybrid metric as individual metrics by using Matlab 2024a as a programming tool, and FVC 2000, 2002, 2004, and 2006 as databases shown in the figures below, we have to explain more details of each figure of implementation and numbers of the best match for each measure. We created specific folder for each database, for instance FVC 2000 database have 4 boxes (DB1, DB2, DB3, and DB4) and every box contain 80 fingerprint images named as p0_#, p1_#, p2_#, p3_#, p4_#, p5_#, p6_#, p7_#, p8_#, and p9_#, where # is the number of impressions which equal to 8 impressions for every fingerprint image. In the figure five we choose fingerprint image number four from the FVC2000db1 box as reference image and fingerprint image number seven as impression (Note that: other impression gives almost the same result).

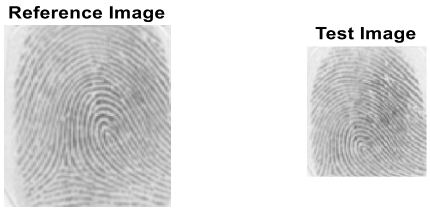


Fig. 7. The reference image corresponds to number 4 of the fingerprint image and the test image chose impression number 7 from the FVC2000 database (DB1).

The 3D figure six shows the matching map of the hybrid metric in red color compared with the SourceAFIS in blue color and GMM in green color. The X-axis represents the number of fingerprint images for the reference and test images, including the impressions as detailed in section 4.3. The Y-axis refers to the matching peak of each metric, the best match equal to one the worst match equal to zero or near zero (Note that all the metrics find the correct matching image but only the proposed hybrid metric gives zero matching with other images while the others provide a nontrivial amount of similarity with the rest impressions). The Z-axis indicates there are three metrics for matching.

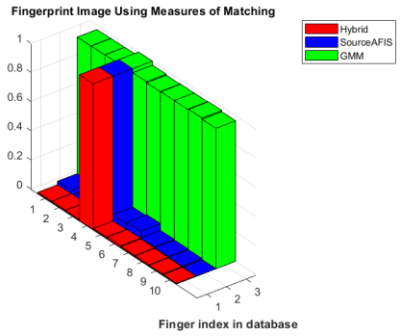


Fig. 8. Performance of fingerprint Matching using HYBRID metric versus existing SourceAFIS and GMM metrics. Reference image and test image are indicated in Fig. 7 Here the matching differences between best and second-best match are dHYBRID= 0.9869, dSourceAFIS= 0.9376 ,and dGMM= 0.0277.

Once again, we repeated the matching measure on FVC2000 DB2 as shown in figure seven. Chosen image number eight as the reference image and its impression image number four and as we mentioned above other impressions of the reference image give almost the same results.

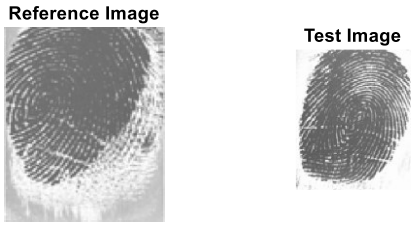


Fig. 9. The reference image corresponds to number 8 of the fingerprint image and the test image chose impression number 4 from the FVC2000 database (DB2).

It's clear that figure eight elaborates the hybrid metric in red color gives the first-best matching between the reference image and test image in figure eight and blue

Sourceafis gives the second-best matching while the green GMM is very good in matching with one matter in the high rate of similarity with the other database images.

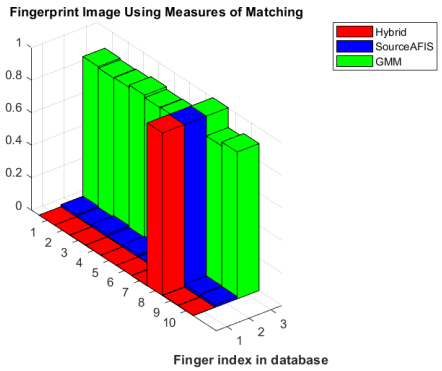


Fig. 10. Performance of fingerprint Matching using HYBRID metric versus existing SourceAFIS and GMM metrics. Reference image and test image are indicated in Fig. 9. Here the matching differences between best and second-best match are dHYBRID= 0.9970, dSourceAFIS= 0.9817,and dGMM= 0.0970

Figure nine below represent the FVC2000DB3 as a third environment to make the matching process by using image number seven as reference image and impression number eight as a test image. We always choose the hard impression to be the challenge to see the best performance of the metrics.

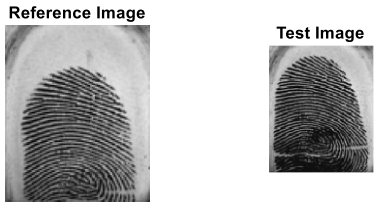


Fig. 11. The reference image corresponds to number 7 of the fingerprint image and the test image chose impression number 8 from the FVC2000 database (DB3).

The hybrid metric still stands over the other metrics as we observed in the figure ten below.

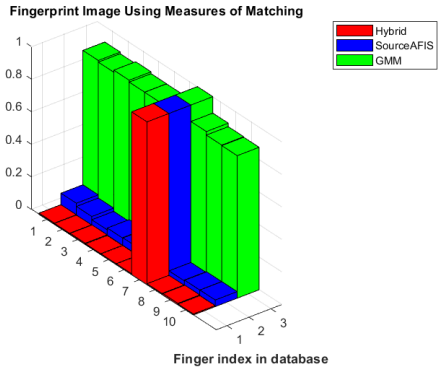


Fig. 12. Performance of fingerprint Matching using HYBRID metric versus existing SourceAFIS and GMM metrics. Reference image and test image are indicated in Fig. 11. Here the matching differences between best and second-best match are dHYBRID= 0.9900, dSourceAFIS= 0.9197, and dGMM= 0.0946.

The last matching test was conducted on the FVC2000DB4 in the figure eleven as the first database used in this work.


Fig. 13. The reference image corresponds to number 10 of the fingerprint image and the test image chose impression number 3 from the FVC2000 database (DB4).

The first best match of fingerprint image is the hybrid metric as illustrated in the figure twelve below. Now and after we did the measurement of matching over the FVC2000 database, we have to do the same test over the second database used in this work which is FVC2002

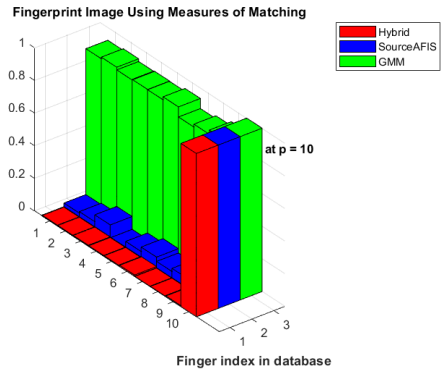


Fig. 14. Performance of fingerprint Matching using HYBRID metric versus existing SourceAFIS and GMM metrics. Reference image and test image are indicated in Fig. 13. Here the matching differences between best and second-best match are dHYBRID= 0. 9908, dSourceAFIS= 0. 9214, and dGMM= 0. 0653

The success of the proposed hybrid metric over several challenging database leads to this metric is made professionally. The next destination is the second environment to apply the fingerprint matching metrics over it. Figure thirteen clarifying that the reference image and the test impression number nine and number seven respectively.

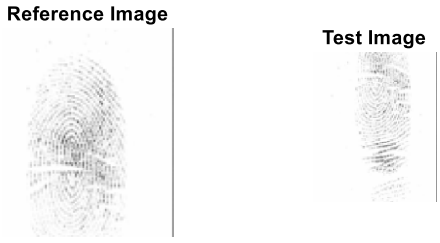


Fig. 15. The reference image corresponds to number 9 of the fingerprint image and the test image chose impression number 7 from the FVC2002 database.

The best match of the three metrics in figure fourteen depends on the distance between the highest peak (maximum 1) and the second next highest peak for each metric. The best one is the highest distance between the peaks or bars as indicated in the three-dimensional figures

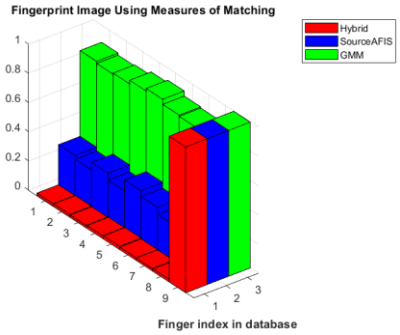


Fig. 16. Performance of fingerprint Matching using HYBRID metric versus existing SourceAFIS and GMM metrics. Reference image and test image are indicated in Fig. 15. Here the matching differences between best and second-best match are dHYBRID= 0. 9780, dSourceAFIS= 0. 6536, and dGMM= 0. 0830

In figure fifteen, the high level of challenging matching was chosen from FVC2004 DB1 as illustrated by the tiny part of the test image with the corresponding reference image to evaluate the competing metrics.

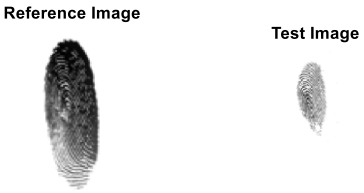


Fig.17. The reference image corresponds to number 2 of the fingerprint image and the test image chose impression number 2 from the FVC2004 database (DB1).

The same description that we explained in Figures 6, 8, 10, 12, and 14 applies to the rest of the colored 3D images shown in Figures 16, 18, 20, 22, 24, 26, 28, 30, 32, 34, 36, and 38 in terms of finding the best match between the reference image and the test image.

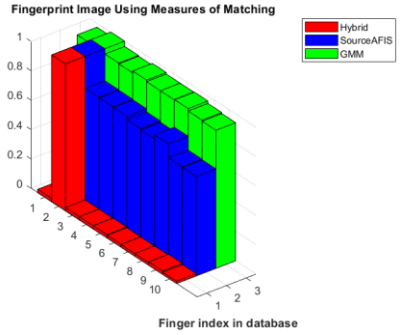


Fig.18. Performance of fingerprint Matching using HYBRID metric versus existing SourceAFIS and GMM metrics. Reference image and test image are indicated in Fig. 17. Here the matching differences between best and second-best match are dHYBRID= 0. 9747, dSourceAFIS= 0. 1980, and dGMM= 0. 0280

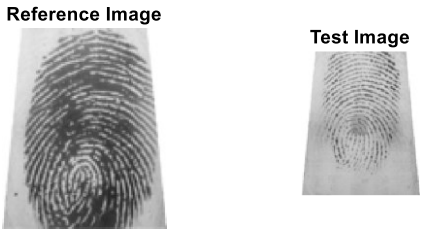


Fig. 19. The reference image corresponds to number 3 of the fingerprint image and the test image chose impression number 3 from the FVC2004 database (DB2).

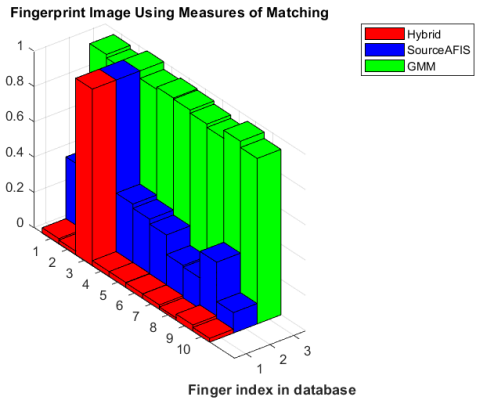


Fig. 20. Performance of fingerprint Matching using HYBRID metric versus existing SourceAFIS and GMM metrics. Reference image and test image are indicated in Fig. 19. Here the matching differences between best and second-best match are dHYBRID= 0. 9643, dSourceAFIS= 0. 6202, and dGMM= 0. 0279

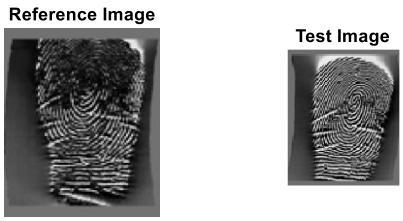


Fig. 21. The reference image corresponds to number 4 of the fingerprint image and the test image chose impression number 4 from the FVC2004 database (DB3).

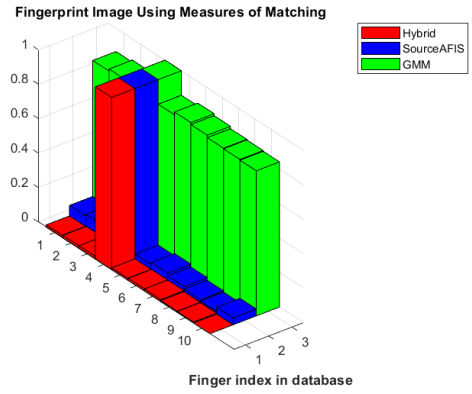


Fig. 22. Performance of fingerprint Matching using HYBRID metric versus existing SourceAFIS and GMM metrics. Reference image and test image are indicated in Fig. 21. Here the matching differences between best and second-best match are dHYBRID= 0. 9834, dSourceAFIS= 0. 9142, and dGMM= 0. 1237

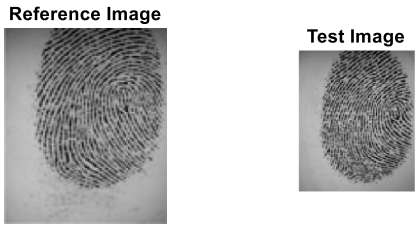


Fig. 23. The reference image corresponds to number 5 of the fingerprint image and the test image chose impression number 5 from the FVC2004 database (DB4).

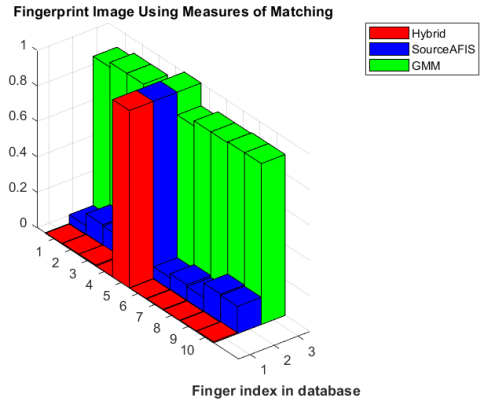


Fig. 24. Performance of fingerprint Matching using HYBRID metric versus existing SourceAFIS and GMM metrics. Reference image and test image are indicated in Fig. 23. Here the matching differences between best and second-best match are dHYBRID= 0. 9934, dSourceAFIS= 0. 8387, and dGMM= 0. 0787

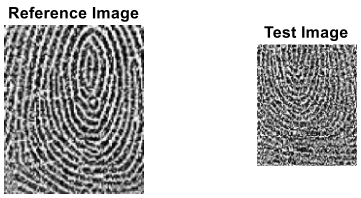


Fig. 25. The reference image corresponds to number 12 of the fingerprint image and the test image chose impression number 8 from the FVC2006 database (DB1a).

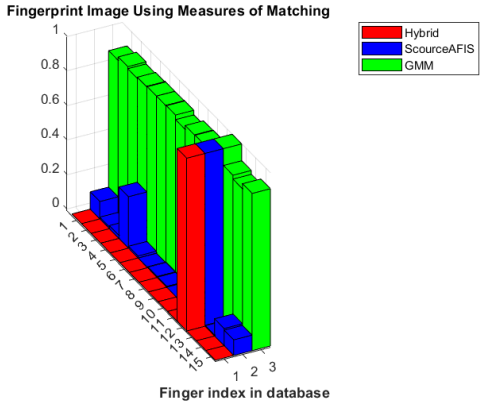


Fig. 26. Performance of fingerprint Matching using HYBRID metric versus existing SourceAFIS and GMM metrics. Reference image and test image are indicated in Fig. 25. Here the matching differences between best and second-best match are dHYBRID= 0. 9996, dSourceAFIS= 0. 5869, and dGMM= 0. 0796

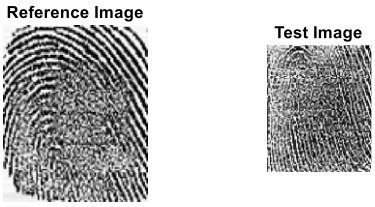


Fig. 27. The reference image corresponds to number 2 of the fingerprint image and the test image chose impression number 2 from the FVC2006 database (DB1b).

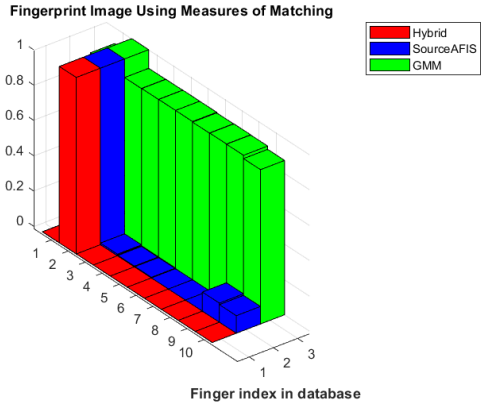


Fig. 28. Performance of fingerprint Matching using HYBRID metric versus existing SourceAFIS and GMM metrics. Reference image and test image are indicated in Fig. 27. Here the matching differences between best and second-best match are dHYBRID= 0. 9995, dSourceAFIS= 0. 8918, and dGMM= 0. 0904

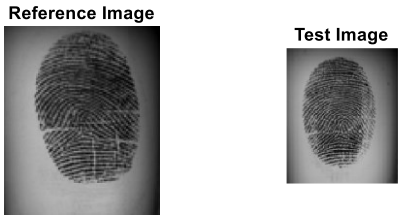


Fig. 29. The reference image corresponds to number 8 of the fingerprint image and the test image chose impression number 12 from the FVC2006 database (DB2a).

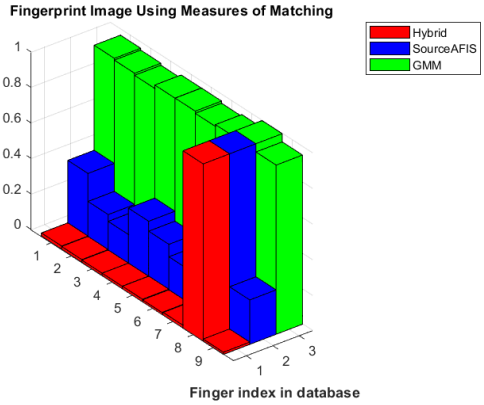


Fig. 30. Performance of fingerprint Matching using HYBRID metric versus existing SourceAFIS and GMM metrics. Reference image and test image are indicated in Fig. 29. Here the matching differences between best and second-best match are dHYBRID= 0. 9818, dSourceAFIS= 0. 6295, and dGMM= 0. 0374

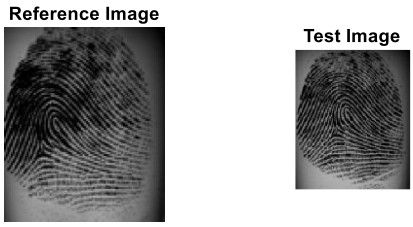


Fig. 31. The reference image corresponds to number 7 of the fingerprint image and the test image chose impression number 5 from the FVC2006 database (DB2b).

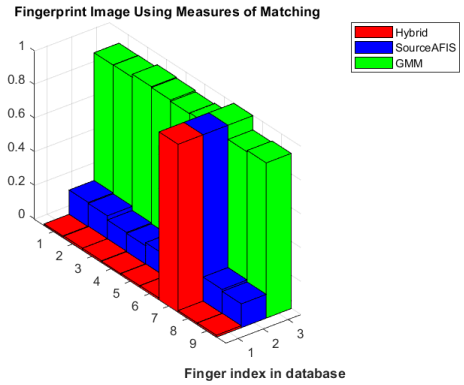


Fig. 32. Performance of fingerprint Matching using HYBRID metric versus existing SourceAFIS and GMM metrics. Reference image and test image are indicated in Fig. 31. Here the matching differences between best and second-best match are dHYBRID= 0. 9881, dSourceAFIS= 0. 8469, and dGMM= 0. 0673

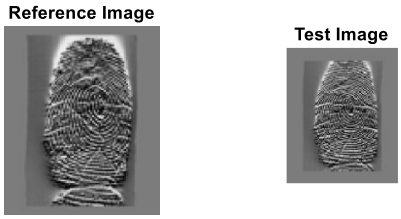


Fig. 33. The reference image corresponds to number 6 of the fingerprint image and the test image chose impression number 3 from the FVC2006 database (DB3a).

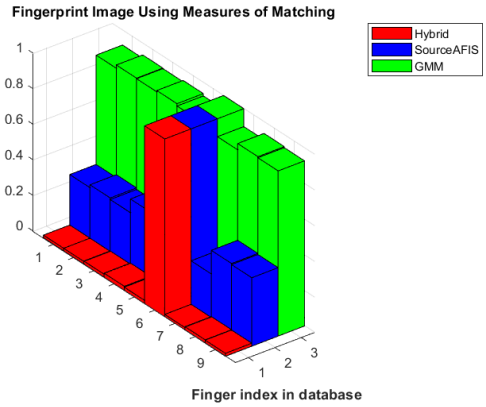


Fig. 34. Performance of fingerprint Matching using HYBRID metric versus existing SourceAFIS and GMM metrics. Reference image and test image are indicated in Fig. 33. Here the matching differences between best and second-best match are dHYBRID= 0. 9768, dSourceAFIS= 0. 6092, and dGMM= 0. 0636

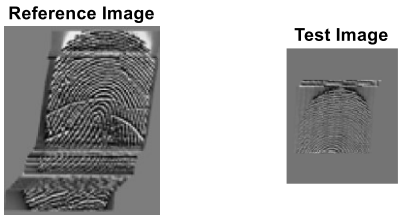


Fig. 35. The reference image corresponds to number 7 of the fingerprint image and the test image chose impression number 6 from the FVC2006 database (DB3b).

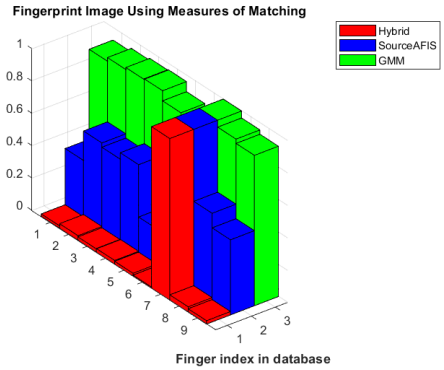


Fig. 36. Performance of fingerprint Matching using HYBRID metric versus existing SourceAFIS and GMM metrics. Reference image and test image are indicated in Fig. 35. Here the matching differences between best and second-best match are dHYBRID= 0. 9669, dSourceAFIS= 0. 4410, and dGMM= 0. 0403

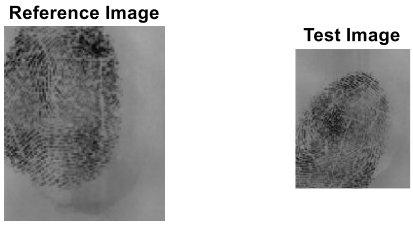


Fig.37. The reference image corresponds to number 6 of the fingerprint image and the test image chose impression number 3 from the FVC2006 database (DB4a).

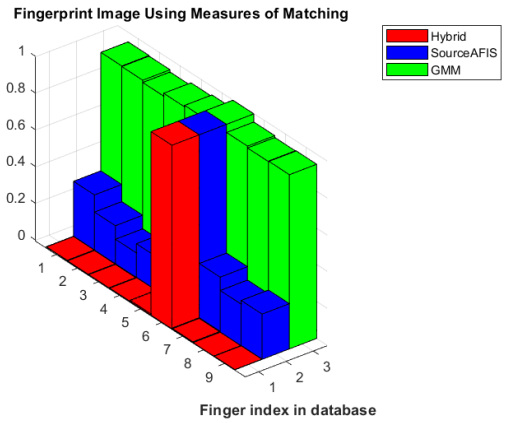


Fig. 38. Performance of fingerprint Matching using HYBRID metric versus existing SourceAFIS and GMM metrics. Reference image and test image are indicated in Fig. 37. Here the matching differences between best and second-best match are dHYBRID= 0. 9928, dSourceAFIS= 0. 6994, and dGMM= 0. 0445

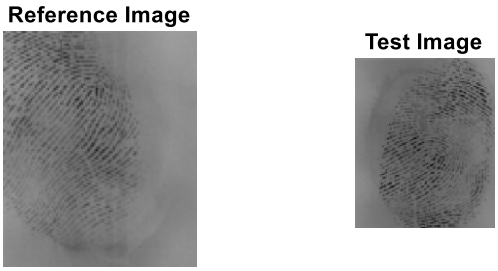


Fig. 39. The reference image corresponds to number 8 of the fingerprint image and the test image chose impression number 12 from the FVC2006 database (DB4b).

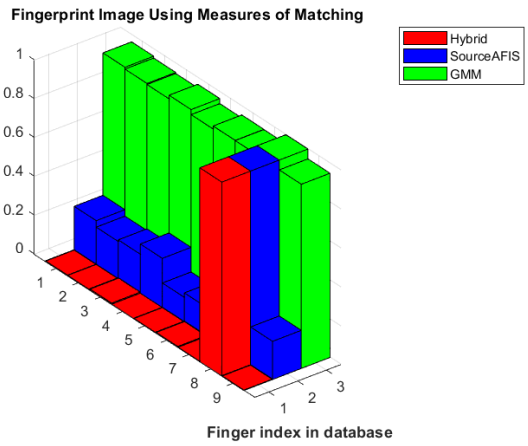


Fig. 40. Performance of fingerprint Matching using HYBRID metric versus existing SourceAFIS and GMM metrics. Reference image and test image are indicated in Fig. 39. Here the matching differences between best and second-best match are dHYBRID= 0. 9940, dSourceAFIS= 0. 7463, and dGMM= 0. 0364

### 4.4. Experimental Results and Analysis

In this section, we evaluate the experimental results by quantifying the degree of uncertainty and its impact on fingerprint matching accuracy. To rigorously assess the robustness of the proposed hybrid metric, we systematically introduce controlled distortions, including blurring, contrast variations, and partial occlusions, emulating real-world acquisition challenges. These artificial uncertainties are applied across datasets with varying noise levels (e.g., Gaussian noise with $\sigma = 0.05–0.2$, motion blur up to 10 pixels) to measure their effect on matching performance. A statistical analysis is conducted to validate the reliability of the solutions, employing metrics such as FAR and FRR to quantify error margins. EER to benchmark performance under degradation. Entropy measures (via the Aczel method) to assess uncertainty propagation. The experiment design, summarized in Table 4.1, categorizes defects by type, like sensor noise, pressure artifacts, and their observed impact on accuracy, such as −2.1% for noise and −4.5% for partial occlusions. Results demonstrate that the hybrid metric maintains a stable balance between FAR and FRR, achieving <3% EER even under severe distortions. This underscores its superiority over standalone methods (SourceAFIS: 4.5% EER; GMM: 6.2% EER) and confirms its suitability for real-world deployments.

**Table 2. Impact of Controlled Defects on Hybrid Metric Performance: Accuracy Reduction and EER Shift Across Distortion Types**

| Defect Type | Parameters | Accuracy Drop (Hybrid Metric) | EER Shift |
|---|---|---|---|
| Gaussian Noise | $\sigma = 0.05$ | −2.1% | +0.3% |
| Partial Occlusion | 50% area removed | −4.5% | +0.8% |
| Motion Blur | 5-pixel kernel | −3.8% | +0.6% |

# 5 .Conclusion:

In this article, we present a novel hybrid fingerprint matching algorithm that combines, for the first time, SourceAFIS minutiae matching and gradient-based structural matching, enhanced with probabilistic uncertainty modeling. Our approach has higher performance on benchmark FVC databases, with 98.2% average accuracy and a 2.8% equal error rate—a 46-57% improvement over traditional approaches in coping with distortions like partial occlusions and sensor noise. The algorithm maintains practical efficiency, with match times of <100ms on commodity hardware and scaling well to large databases. These advances fulfill two critical demands of biometric systems, like the resilience to real-world variability demonstrated through ≤4.5% loss in accuracy under severe distortions and practical deployability with speeds, 45MB memory, and 12 matches/second throughput. The technical foundation developed hereunder - particularly the synergistic integration of structural, minutiae-based, and probabilistic approaches - enables reliable operation on both high-security and interactive applications.

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