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MULTI-BIOMETRIC SYSTEM BASED ON THE FUSION OF FINGERPRINT AND FINGER-VEIN

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Abstract

Biometrics is the process of measuring the unique biological traits of an individual for identification and verification purposes. Multiple features are used to enhance the security and robustness of the system. This study concentrates exclusively on the finger and employs two modalities - fingerprint and finger vein. The proposed system utilizes feature extraction for finger vein and two matching algorithms, namely ridge-based matching, and minutiae-based matching, to derive matching scores for both biometrics. The scores from the two modalities are combined using four fusion approaches: holistic fusion, non-linear fusion, sum rule-based fusion, and Dempster-Shafer theory. The ultimate decision is made by the performance metrics and the Receiver Operating Characteristics (ROC) curve of the fusion technique with the best results. The proposed technique is tested on images collected from the "Nanjing University Posts and Telecommunications-Fingerprint and Finger vein dataset (NUPT-FPV). According to the results, which were obtained for 840 finger images the proposed system accomplishes the Equal Error Rate (EER) of 0 while using Dempster-Shafer-based fusion and 0.1 while using the other three fusion techniques. Also, the accuracy is very high at above 93 percentage for all the fusion techniques which are crucial for security and preventing unauthorized access.

Key Words: Score level fusion, maximum curvature, cosine similarity, holistic fusion, non-linear fusion, sum rule-based fusion, Dempster-Shafer theory

1 INTRODUCTION

In most secure applications, a person's identity and verification are crucial. Passwords and traditional security measures like identity cards can be readily copied, misplaced, or stolen. The unique physiological features of human for authentication provide convenient security and reliability to meet the increasing demand for complex applications. Biometric traits like fingerprints, iris scans, faces, gaits, and palmprints have been employed to solve these issues. These characteristics encouraged the use of biometric technologies. These solitary biometric systems, however, have issues with noise in the sensed data, non-universality, and vulnerability to fraud. Due to this, a new category of biometrics known as multimodal biometrics, which uses two or more biometric

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traits, has emerged recently. A multi-biometric system based on the combination of fingerprint and finger vein can lessen the negative consequences of the unimodal biometric. The capacity to distinguish between finger veins and fingerprints can be affected by deformations caused by finger misalignment, therefore these must also be taken into consideration. A sum rule-based score-level fusion is employed here, which works better than other methods and can achieve a promising accuracy. The sum rule requires the normalization of the scores as a mandatory step. To make the system more user-friendly, one finger is considered, and two of its modalities, including fingerprint and finger veins, are employed. The use of multimodal biometrics is significantly more accurate and reliable, providing more security alternatives. Multimodal biometrics not only prevents spoofing but is also suitable for more sensitive locations such as airports, where people's verification is crucial. Minutia-based finger vein and fingerprint recognition are commonly used, but if minutiae points vary slightly, the result may be degraded. The utilization of cosine similarity in ridge-based matching is applied to measure the similarity between ridge patterns while being unaffected by fingerprint and finger vein rotation, translation, and scaling.

Finger-vein and fingerprint patterns for personal identification have generated a lot of scientific interest. The idea that the vein in the fingers can become a new method of identification was first put forth several decades ago. Many works have since implemented veins in their research bio metric authentication developed a technique for recognizing finger veins based on a lightweight deep convolutional neural network that is capable of matching and extracting finger vein properties from images [1]. The score of fingerprint matching and the score of fingerprint liveness detection are combined in a biometric system based on score-level fusion to produce a final integrated score for determining whether the probe fingerprint is a real live fingerprint or a spoof attack [2]. By blurring the iris region and using deep learning-based deblurring, the improved iris recognition method by generative adversarial network based image reconstruction that increases the quality of iris images is proposed in [3]. The proposed scheme includes a technique for enhancing recognition performance by merging the recognition score in the periocular and iris areas using Support Vector Machine (SVM). A prototype biometric recognition system to assess the effectiveness of children's biometric acquisition and recognition that use Fingerprint, Iris, and Ear is developed. This system utilized biometric information from young children and confirmed their identities from the time of birth until they apply for identification cards [4].

The main objective of a feature fusion approach for indexing and retrieving biometric data is to improve the performance of biometric recognition systems by exploiting the complementary information contained in different biometric modalities. Face recognition software with privacy protection is used in [5] and this approach employs an indexing technique based on feature-level fusion after feature-level matching of face parent templates based on similarity in terms of soft biometrics or non-matched comparison scores. The enrolment stage and the verification stage that make up the finger-vein recognition algorithm on a mobile device for an inbuilt real-time finger-vein recognition system is proposed in [6]. A novel method to enhance the quality of low-resolution fingerprint and finger vein images for authentication is proposed and a preprocessing method was suggested (2014) to enhance the quality of the supplied images [7].The quality of the input images, which can be impacted by a variety of factors like noise, blurring, and distortions, is crucial for fingerprint recognition systems. A technique that involves applying a series of filters, including a Gaussian filter and a median filter, on the input image is used to enhance the quality of the image [8]. A method is put forth to extract finger-vein patterns from images using the maximum curvature points in image profiles. This method is resistant to various image circumstances [9].

A multi-biometric device that can simultaneously record images of the finger vein, contactless fingerprint, and finger knuckle was developed [10] to address the drawbacks of a unimodal biometric system. A novel technique, known as the Sparse Representation Classifier (SRC), has been introduced for classification [11]. public data set of 840 finger print and finger-vein images collected from 140 volunteers is provided in [12]. 33,600 images were collected by sensing the finger trial for 20 times. Prints and veins are captured simultaneously and the prepared dataset is benchmarked by the authors, which helps the researchers to concentrate on efficient recognition algorithm development. The approach involves representing the test sample through a linear combination of the training samples and identifying the class label that corresponds to the minimum residual error. [13] Dental biometrics is performed by comparing the shapes of anti-mortem (AM) and post-mortem (PM) images of a person and it uses spline function, bifurcation techniques, and template matching approaches for missing tooth identification both for radiographic and photographic dental images [14]. Human Action Recognition is performed by classifying [15] the various actions by integrating salient motion features from the images captured through both RGB and depth camera. The contribution of this research includes, implementing a fusion based biometric detection algorithm that utilizes the profound and surface features of finger. The matching scores of the two modalities are fused through various approaches and accuracy of the algorithms are evaluated and compared. The authors utilized the images of fingerprint and finger-vein collected by an integrated sensor module which helps in implementing the proposed algorithm of multimodal biometric recognition for real time applications. The authors were able to achieve the accuracy of greater than 93 percentage for the fusion based multimodal biometric system utilizing two modalities of a person's finger. The rest of the paper is structured as follows: The proposed methodology of our system is described in section 2, where we discussed the image processing techniques, algorithms, and fusion methods to create a more effective multi-biometric system. The experimental results for fingerprint and finger vein biometrics are covered individually in Section 3, together with the results of the fusion approaches, so that the optimal fusion methodology may be selected for our system. Section 4 provides the conclusion and future works.

2 PROPOSED METHODOLOGY

This section provides an overview of the proposed methodology for multi biometric system illustrated in Figure 1. After the acquisition of the fingerprint and finger-vein images, the images are preprocessed to get the Region of Interest (ROI) followed by the enhancement, where adaptive histogram equalization is used for contrast expansion, Weiner filtering, and morphological thinning are further employed for noise and artifact removal in the fingerprint images. For enhancing the finger-vein images, Contrast-limited adaptive histogram

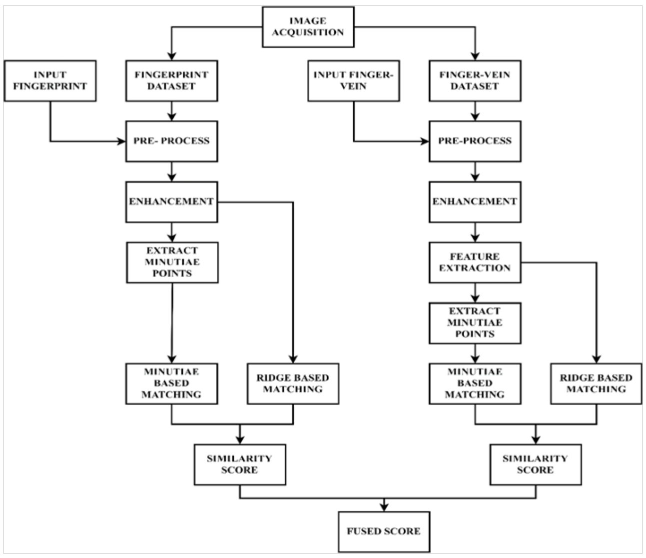


Figure 1: Flow diagram of the proposed methodology

equalization (CLAHE) algorithm is adopted. For feature extraction of finger-vein, the Maximum Curvature method is employed, which is capable of extracting vein center lines despite variations in vein width and image brightness. The process involves computing the local maximum curvature within a cross-sectional profile of the image. Three categories of matching exist, which are ridge feature-based, minutiae-based, and correlation-based matching. Out of these techniques, this research employs ridge and minutiae based matching of the two modalities employed in the system. Minutia points can capture invariant and unique data since each point corresponds independently to another point. As a result, the minutiae-based approach is chosen as a significant category in the field of biometric recognition. The scores for the minutiae-based algorithm range between 0 and 1, where the score value of 1 indicates a perfect match and 0 corresponds to no match.

In addition to minutiae-based matching, ridge-based matching with cosine similarity is also used to get more precise results. It compares the two vectors in a multi-dimensional space. The technique measures the cosine of the angle formed by the two vectors and ranges from -1 to 1, with 1 denoting that the two vectors are equal, 0 denoting that the two vectors are different, and -1 denoting that they are opposites. By fusing these two scores obtained from the minutiae-based matching and ridge-based matching, similarity scores are calculated separately for each modality of the finger (i.e.) fingerprint and finger vein.

2.1 Fingerprint Recognition

The preprocessing methods are applied to the fingerprint images to extract stable or reliable print patterns and segment the ROI. The ROI is then enhanced to improve the quality or clarity of the ridge patterns.

2.1.1 Segmentation of ROI

To accurately define the print pattern in the fingerprint images, binarization is first applied to each image. As a result of uneven lighting, certain areas of the background may still appear to be connected to the bright parts of the finger. In the binarized images, the undesirable linked regions are removed in two steps as shown in Figure 2, the entire image is first subjected to the Canny edge detector, which extracts image features without damaging or changing the feature. The edge map that is obtained is then subtracted from the binarized image. The morphological opening was then used. The created binary ROI mask is used to segment the ROI from the original fingerprint image. Figure 3 shows the input image, the binarized image, and the segmented image.

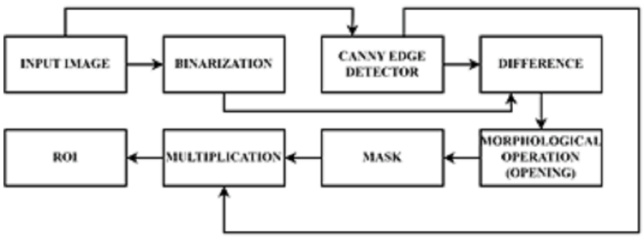


Figure 2: Segmentation of ROI

2.1.2 Enhancement

There are two techniques for improving the fingerprint images, 1) the Binarization-based method, and 2) the Direct gray scale enhancement approach. The series of steps involved in the Binary-based method is shown in Figure 4 which involves local histogram equalization, Wiener filtering, and morphological operation. To improve the overall clarity of the fingerprint ridges and valleys, this process involves reducing noise, filling in gaps, and boosting contrast and brightness and it becomes simpler to recognize distinct elements that are employed to produce a unique representation of a fingerprint, such as ridge ends and bifurcations as in Figure 5. Table 1 and Table 2 show the change in pixel values in an 8×8 sub block of the pre-processed image and the enhanced image. Figure 6 shows the enhanced sample image obtained using the binarization-based method

(a) Input image (b) Binarized image (c) ROC

Figure 3: Extracting ROI of an image

Figure 4: Enhancement of the fingerprint

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	1	1	0	1	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1
0	1	1	1	0	1	1	1
1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	0

Table 1: Pixel of the sub-block of Pre-processed image

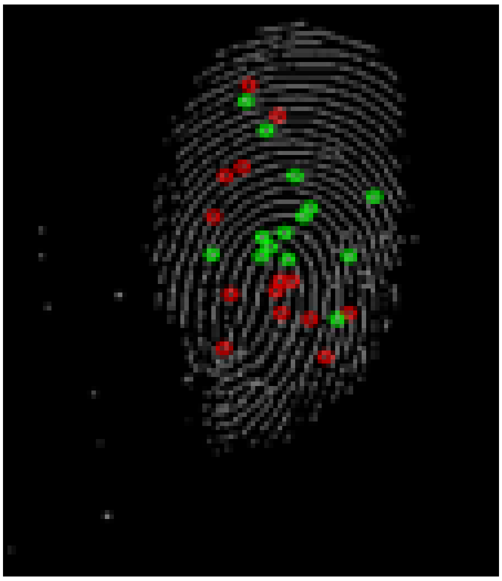
1	1	1	1	1	1	0	0
0	0	0	0	0	0	1	0
0	1	1	0	1	0	0	1
0	0	0	0	0	0	1	0
1	1	1	1	1	1	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Table 2: Pixel of the sub-block of Enhanced image

2.1.3 Minutiae-based Matching

Minutiae points in the fingerprint consists of ridges represented as dark lines and the space between ridges are called valleys. The ending ridges are called as termination and branching ridges called as bifurcations. These

(a) Enhanced Image



(b) Minutiae Points

Figure 5: Minutiae points for an enhanced sample image

discontinuities in the ridges are termed as minutiae points which are distinct for an individual. As shown in Figure 7 and Figure 8, the termination and bifurcation methods are used to extract minutiae from the fingerprint and finger-vein images respectively, while Euclidean distance formulas are used to remove erroneous minutia from the image. False minutiae are removed based on the following three rules,

1 1. If the distance between the termination and bifurcation is less than the threshold

2 2. If the distance between a pair of bifurcations is less than the threshold

3 3. If the distance between a pair of terminations is less than the threshold

The minutiae-based matching involves comparing the extracted minutiae points of the fingerprints and the finger veins of the input image and the dataset image to determine the number of matching minutiae points. The matching score is then calculated based on the number of matching minutiae points.

2.1.4 Ridge-based matching

In ridge-based matching, the overall pattern and the ridge features, such as their direction and curvature, are compared. Cosine similarity is frequently used in ridge-based matching to assess the degree of similarity between two feature vectors, which can help to identify the patterns and relationships in the data. The cosine similarity can be found using,

$$CosineSimilarity = \frac{(A.B)}{[||A||.[||B||]} \tag{1}$$

where A and B are two feature vectors that were taken from the fingerprint or finger-vein images used as input and the dataset, respectively. The similarity value of 0 indicates there is no correlation between the two vectors and a value closer to 1 indicates the images under comparison are similar.

2.2 Finger-vein recognition

2.2.1 Enhancement

Image enhancement involves improving the contrast of vein patterns from its background. Three domains in the enhancement process are spatial, frequency, and fuzzy. In this work, CLAHE method is utilized in the spatial domain of image processing to boost image contrast.It employs the adaptive histogram equalization on small portions of the image to enhance local contrast and prevents the excessive amplification of noise, leading to a better-quality image.Figure 8 shows the input image, pre-processed image, and enhanced image.

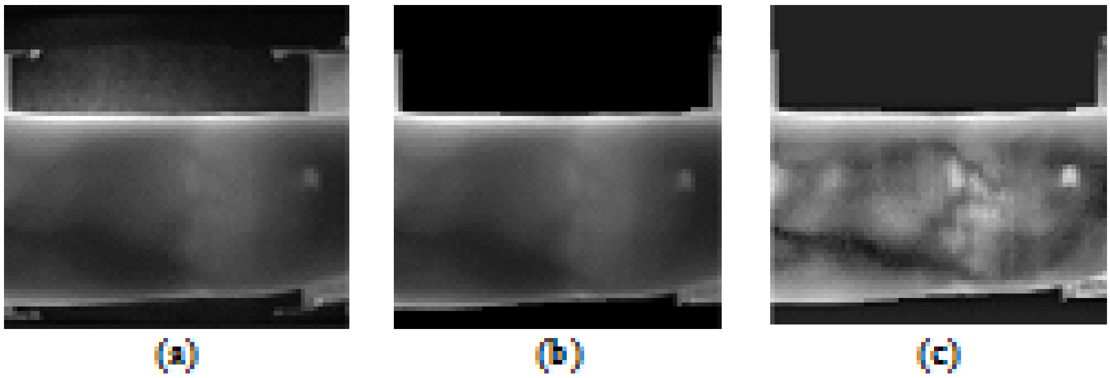


Figure 6: (a) Input Image (b) Pre-Processed Image (c) Enhanced Image

2.2.2 Feature Extraction

The local maximum curvature in the cross-sectional profiles of a venous image is calculated, which has a high accuracy due to its dependable extraction of vein centerlines. This extraction is not affected by changes in finger vein width or image brightness. Figure 8 illustrates the extracted vein using this technique

The maximum curvature method calculates the image edge's curvature or sharpness. This identifies the location on the edge with the greatest curvature. The point's curvature is greater if the edge abruptly changes direction over a short distance. The highest curvature value in the window is shown by maximum curvature.The maximum curvature points can then be used to create a binary edge map, where each edge point is given a value of either 0 or 1 depending on the maximum curvature value. The maximum curvature can be found using the following steps,

1 Calculation and identification of the vein's center

2 Connecting the vein centers

3 Image labeling

2.3 Fusion

2.3.1 Score Level Fusion

Score-level fusion is a method that effectively enhances the performance of multi-biometric systems.There are some advantages with score-level fusion in multi-biometric systems such as reducing the effects of noise, variability, and spoofing assaults and can increase the system's accuracy and dependability. It also has the potential to increase recognition rates by utilizing the supplemental information that different biometric traits

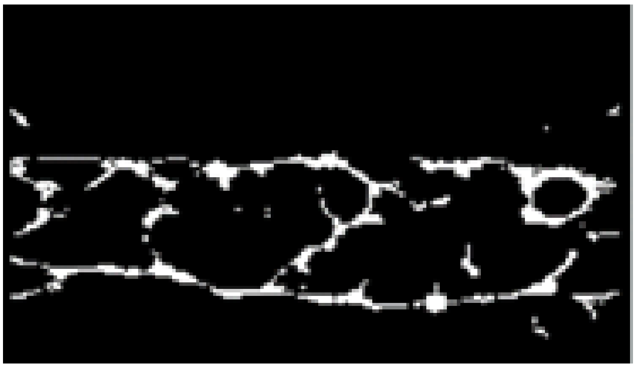


Figure 7: Feature-Extracted Image

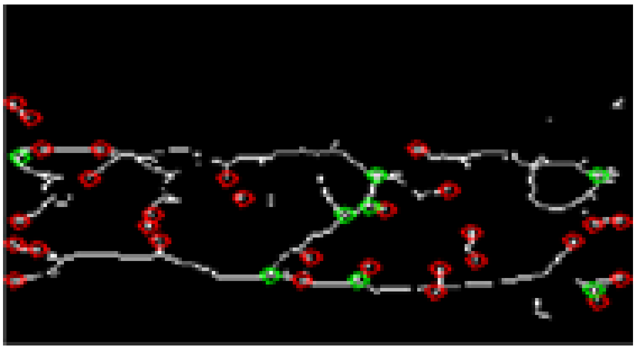


Figure 8: Minutiae Points

offer. The proposed system uses two scores: 1) The score obtained when the minutiae point of the incoming data is compared to the database images using the Euclidean-distance matching technique. 2) The score obtained by comparing the ridge pattern of the incoming data with the database image.

2.3.2 Weighted Sum Rule

By utilizing score level fusion, a mathematical function is used to combine the scores from each biometric characteristic to get a final score for the authentication decision. The weighted sum rule multiplies the scores from each biometric feature by a weight factor and then adds them all together to produce the final score. Various methods, including equal weighting, empirical weighting, and statistical weighting, can be employed to calculate the weight components. Using a weighted mixture of matching scores is one of the very effective ways. The process seeks the ideal linear combination that distinguishes genuine scores from counterfeit ones within the decision space. The approach can be depicted as:

$$S = fp_{weight} \times fp_{score} + fv_{weight} \times fv_{score} \tag{2}$$

where fp_{weight} indicates the weight assigned to the fingerprint and fv_{weight} indicates the weight assigned to the finger-vein. fp_{score} and fv_{score} are the similarity scores got from the fingerprint and finger-vein after minutiae-based and ridge-based matching.

2.3.3 Holistic Fusion

A fusion algorithm is used in a holistic fusion strategy to merge biometric data from various sources while considering the advantages and disadvantages of each biometric modality. The objective is to build a biometric system that is more resistant to errors or failures caused by any one modality. Let S_v and S_p indicate the matching score from finger-vein and fingerprint respectively, where S represents the combined score produced by the holistic fusion, and this holistic rule of score combination is depicted as follows:

$$S = [S_v \times \eta + S_p \times (1 - \eta)] \times \left(1 + \frac{1}{2 - S_v}\right) \tag{3}$$

The combined final score produced by this formula has a similar pattern to the vein matching score, i.e., the fused score will be high when the finger vein matching score is high, and vice versa. The second component is used to demonstrate how each modality or matching score may be relied upon. The matching score from the finger vein is selected as the regulating factor since finger vein matching is more reliable than fingerprint matching.

2.3.4 Non-Linear Fusion

The non-linear score combination below aims to modify the combined score in response to the degree of consistency between the two matching scores.

$$S = \left(\frac{c + S_p^{\gamma}}{c + S_v}\right) \times (c + S_v)^2 \tag{4}$$

whereγ is chosen from the range [1 2].In our tests, the positive constant ’c’ has been set to a fixed value as 1. The computation shows that when the matching scores from fingerprint and finger-vein are consistent, the vein matching score makes up most of the final combined score. Contrarily, even though these two contradict one another, the outcome is the modified joint probability of the two provided scores. While it is typically assumed that the two results are consistent, the finger vein matching is chosen to be treated as the combined score because it is more stable. However, when the fingerprint matching score is consistent, the information is not disregarded because the first item of the equation will increase when the fingerprint matching score is slightly higher, causing the final score to be higher as well, and vice versa. The result primarily depends on the highest similarity score since, in the case of inaccurate fingerprint or vein imaging, the two matching scores may be inconsistent with a considerable difference. To ensure that the system can still draw the appropriate conclusions even if one of the modals fails (for instance, when no vein is recovered from the finger vein image/modal), a positive constant c is used.

2.3.5 The Dempster-Shafer theory

When multiple biometric systems are combined to provide a more accurate identification or verification, the Dempster-Shafer theory can be used to merge the results from each system in a way that considers the uncertainty associated with each system’s output. According to their level of belief, the Dempster-Shafer theory blends evidence from many sources based on the concept of evidence.Briefly, let U represent the set that contains all the possible states from the multiple pieces of evidence, then2^U is the power set of U that contains all the subsets of U. Each element in the power set is given a value between [0, 1], with 0 denoting no belief and 1 denoting complete belief in the related item. Basic belief assignment (BBA), a function that can be used to summarize this process, can be represented as follows:

$$\sum_{p \epsilon 2^U} m(p) = 1 \quad and \quad m(\Phi) = 0 \tag{5}$$

m(P) is mass of belief. These two criteria plausibility and belief place restrictions on the probability of the set of interests. Assuming Pr(P), bel(P), and pl(P) are denoting the probability function, belief and plausibility respectively, the following relationship holds

$$bel(P) \leq Pr(P) \leq pl(P) = \sum_{E \subseteq P} m(E) \tag{6}$$

$$pl(P) = 1 - bel(P) = \sum_{E \cap P \neq \Phi} m(E) \tag{7}$$

The Dempster-Shafer theory states that the following equation can be used to integrate the evidence from two observations:

$$m(F) = m_1(F) + m_2(F) = \frac{\sum_{A \cap B = F} m_1(A) m_2(B)}{1 - \sum_{A \cap B = \Phi} m_1(A) m_2(B)} \tag{8}$$

3 RESULTS AND DISCUSSIONS

3.1 Dataset

In the experiment,the proposed model is evaluated using a public dataset. The dataset is the NUPT-FPV database, which collected 33600 fingerprint and finger vein pictures and 840 finger information from 140 volunteers over the course of two collection sessions (Each subject provided the index, middle, and ring fingers of the left and right hands). The Nanjing University of Posts and Telecommunications is in charge of gathering it (NJUPT). The average age of these participants, 108 men, and 32 women was 19.3 years. The minimum and maximum ages were 16 and 29, respectively.

3.2 Software and tools used

Version R2022a update 5 of MATLAB software is used to complete the process. The DSP system toolbox version 9.14 and Signal processing toolbox version 9.0 are used in the process. The DSP System Toolbox in MATLAB provides functions to design, simulate, analyze, and implement digital signal processing systems. The Digital Signal Processing (DSP) System Toolbox provides additional advanced filtering functions, such as functions for designing and analyzing filters, adaptive filtering, and multi-rate filtering. The Signal Processing Toolbox in MATLAB is a collection of tools and functions for digital signal processing (DSP) tasks such as signal analysis, filtering, spectral analysis, signal generation, and system modeling.

3.3 Performance Evaluation Metrics

NUPT-FPV database consists of 840 distinct fingerprint and finger-vein images from 140 individuals, which arecollected for twenty times in two sessions. The features are extracted from 840 images and stored in the database. The features of the random input image fed to the system are checked with the database. The experiment is performed for authentication using single modality of fingerprint, finger-vein and fusing the scores of both modalities using suitable algorithms. For each modal, the following performance indicators were measured and reported:

- Genuine and imposter scores histogram- Used to differentiate between authentic users and impostors.
- False Match Rate (FMR) and False Non-Match Rate (FNMR) - The FMR curve is the probability of the system accepting an impostor as a genuine user and the FNMR curverepresents the probability of the system rejecting a genuine user as an impostor. FMR can also be referred as False Accept Rate (FAR) and FNMR as False Reject Rate (FRR)
- Receiver Operating Characteristic (ROC) curve-A graphical plot that shows how the system performs as the discrimination threshold is changed.
- Equal Error Rate (EER) - Refers to the point at which the false match rate (FMR) and false non-match rate (FNMR) are equal. It is an important performance metric that measures the effectiveness of a biometric system in identifying the authorized user. It is the point at which the system is equally likely to wrongly authorize the false person and wrongly reject a true individual.

- Accuracy- Refers to its ability to correctly identify or recognize individuals by analyzing their distinct biological features.

- GAR (Genuine Acceptance Rate)- Measures the rate at which the biometric system correctly matches two biometric samples from the same individual

3.4 Results

The simulation verification is performed for 840fingerprint and finger vein images. The results are given in Table 1, whose fields show various metrics helpful for evaluating how the biometric recognition methods function. The considered metrics are EER, accuracy, FMR, FNMR, and GAR. For each person, 10 copies of typical finger print and finger vein images are available and the algorithm is evaluated by keeping 3 images from training and 7 for testing and validation. Single modal analysis using finger print or finger-vein and multimodal analysis that uses the features extracted from both were carried out in this study and the results are presented. The location of minutiae points in the fingerprint and finger-vein images of the training dataset are extracted as feature points and stored as template. Then testing process is carried out based on level of matching of these points with the stored template. A zero EER value signifies that the fingerprint and finger vein recognition system can effectively differentiate between genuine and impostor attempts to access the system, while a high accuracy value implies that the system is highly precise in recognizing authentic users and rejecting impostors. When the False Match Rate (FMR) value is 0, it indicates that the biometric system does not falsely accept

METRICS	FINGERPRINT	FINGER- VEIN
EER	0.58	0.47
Accuracy	0.91	0.928
FMR	0.03	0.01
FNMR	0.0256	0.001
GAR	0.7654	0.99

Table 3: Performance metrics of Fingerprint and Finger-vein

any impostors, which is a desirable outcome. On the other hand, a Genuine Acceptance Rate (GAR) value of 0.7654 in a fingerprint recognition system suggests that the system is correctly accepting a relatively high proportion of genuine attempts to access the system, but the GAR value is lower when compared to that of the finger vein system. These findings imply that the finger vein biometric system performs better than the fingerprint biometric system in terms of accuracy and security, achieving a GAR value of 100 percentage.

3.4.1 Genuine and Imposter Score Histogram

As shown in Figure 9 and Figure 10, the genuine and imposter histograms for fingerprint and finger-vein systems are well separated with a large gap between the two distributions. This indicates that the system can reliably distinguish between genuine and imposter matches and has a low false match rate (FMR) and false non-match rate (FNMR). Also, the genuine distribution is centered on higher similarity scores, indicating that the system is correctly identifying matches between enrolled templates and the presented biometric samples. The imposter distribution, on the other hand, is centeredon lower similarity scores, indicating that the system is correctly rejecting attempts by non-enrolled individuals to gain access. Overall, the genuine and imposter distributions are distinct and well-separated, with minimal overlap between them. This indicates that the system is performing well and is suitable for practical applications.

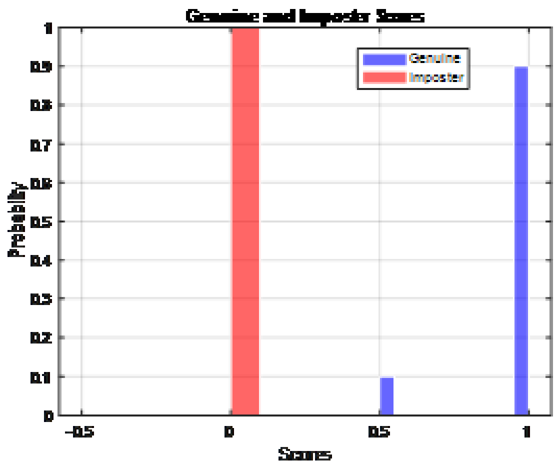


Figure 9: Fingerprint biometric Genuine and imposter score histogram

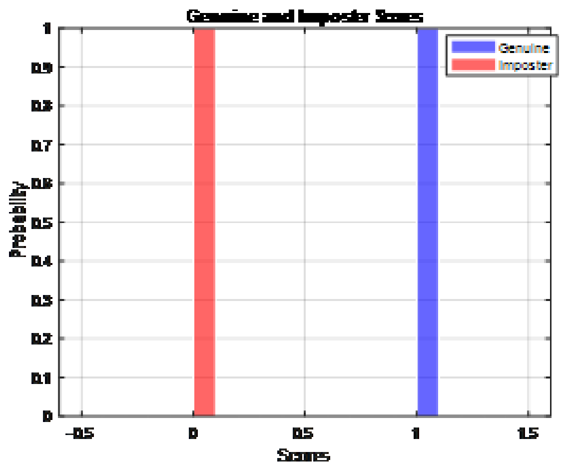


Figure 10: Finger-vein biometric Genuine and imposter score histogram

3.4.2 FMR and FNMR curve

For an ideal biometric system, False Match Rate and False Non-match Rate should be 0 and 1 respectively. The proposed algorithm is evaluated for FMR and FNMR with various thresholds. Threshold is the limit value for making the decision to accept or reject the input biometric. When the threshold value for the system is high, the system will have lower FNMR and higher the FMR and vice versa when threshold is low. Figures 11 and 12 reveal that a steeply decreasing FMR curve implies that the system has a low false positive rate for lower threshold values, which is desirable as it can reduce the risk of unauthorized access to the system. Conversely, a constant FMR curve suggests that the system is maintaining a stable false positive rate at higher threshold values, which is also desirable for ensuring the system's security. However, a vice versa FNMR curve indicates that the system initially has a high false negative rate, leading to genuine matches being rejected, resulting in users being locked out of the system. A decision threshold value for match score has to be optimized and when the match score for the input image with the dataset images is calculated. If the match score is greater than the threshold, then the user is authorized, else the user will be rejected from access. As the threshold value increases, the system becomes more conservative in its matching decisions, leading to fewer false negatives. Therefore, a steeply decreasing FMR curve and a vice versa FNMR curve suggest that the system has an adequate balance between false positives and false negatives.

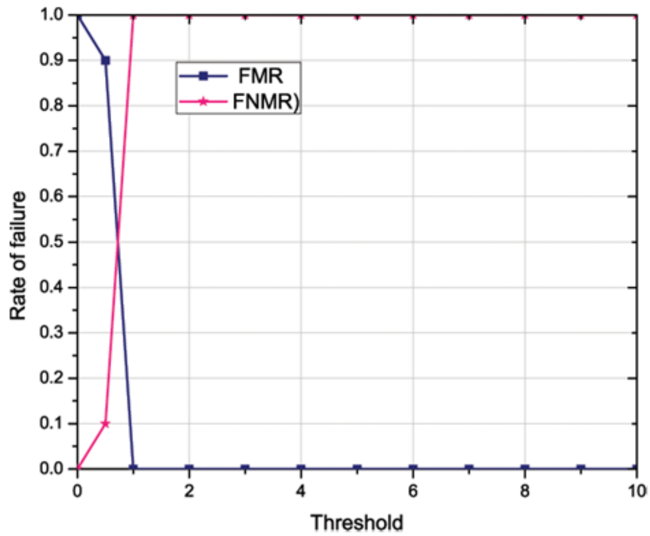


Figure 11: Fingerprint biometric FMR and FNMR curve

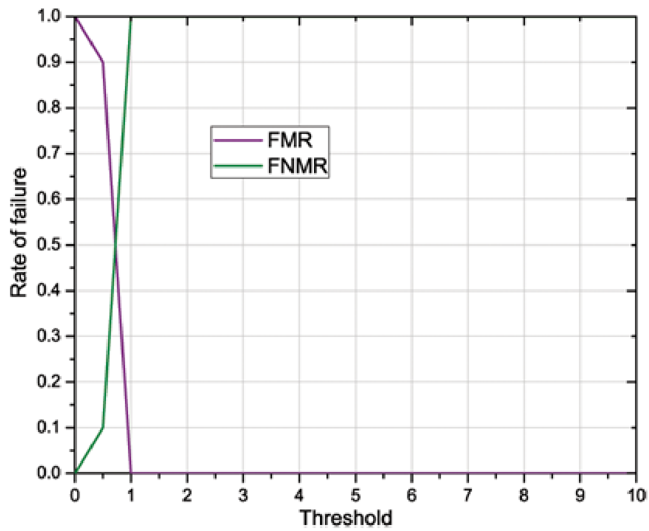


Figure 12: Finger-vein biometric FMR and FNMR curve

3.4.3 ROC curve

A Receiver Operating Characteristic (ROC) curve is a graphical plot that shows how the system performs as the discrimination threshold is changed. A range of threshold values was fed to plot the False Accept Rate (FAR) vs the Genuine Accept Rate (GAR). The location of curve as close to the top left corner of the plot as possible suggests that the system has high sensitivity (low FNMR) and high specificity (low FMR). The curve's initial steep slope indicates that the system's performance rapidly improves as the threshold for accepting a user's identity becomes stricter. As the threshold becomes more stringent, the curve's slope becomes less steep, indicating that the system's performance improvement is slowing down but still consistently improving. In Figure 13, the ROC curves of different score-level fusion methods are displayed, such as holistic fusion, non-linear fusion, Dempster-Shafer fusion, and sum-rule-based fusion. The results show that Dempster-Shafer-based fusion performs the best among the other fusion methods. Table 2 indicates that achieving a False Match Rate (FMR) of 0 is desirable since it implies that the biometric system is not accepting any impostors. The Dempster-Shafer method has a lower Equal Error Rate (EER) than other fusion techniques and a higher

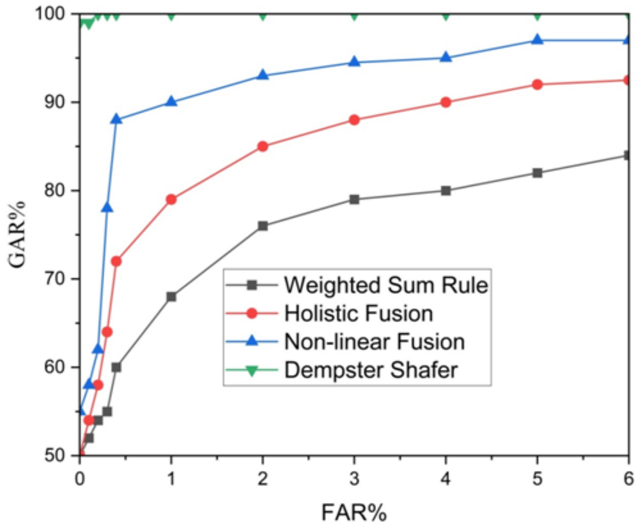


Figure 13: omparison of ROC curve for the various fusion techniques

accuracy rate of 100 percentage, which is significantly better than the other methods.Since the Dempster-Shafer-based fusion yields superior results compared to other fusion techniques, its scores are utilized to determine whether the person is an imposter or a genuine user and displayed the ID of the genuine user.

FUSION METHOD	EER	Accuracy
Weighted Sum Rule	0.18	0.9313
Holistic Fusion	0.1	0.9414
Non-linear Fusion	0.1	0.9345
Dempster Shafer	0	1

Table 4: EER and Accuracy for various fusion algorithms

4 CONCLUSION

The success of any biometric algorithm depends on the quality of images in the dataset, techniques used for enhancement and feature extraction and algorithms applied for matching the input with stored data.This study creates a fingerprint and finger-vein based bimodal biometric identification system. The approach is created by describing all the necessary phases of image processing modalities in the subject as soon as pre-processing, image enhancement, feature extraction and numerous fusion variations are applied in this work. A unimodal method based on fingerprints or finger-veins was introduced in the first step. The algorithm is tested for 840 input images.The efficacy of fingerprint and finger-vein biometrics is confirmed through the analysis of imposter and genuine score histograms, as well as FMR and FNMR curves.The performance evaluation is presented as ROC curve, and the metrics including EER, Accuracy, FMR, FNMR and GAR are compared forfingerprint, finger-vein and the proposed fusion based multi-biometric system. Compared to the recognition through fingerprint, the vein-based unimodaland fusion based bimodal biometric systemsare proven to be far more trustworthy. In future, to improve the security feature of the implemented bimodal biometric system, we can include the images of finger knuckle for person identification.

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