Feature Level Fusion of Palmprint and Iris Images for Person Identification

May Essam, Fayez Wanis Zaki, Ervat El Seddek

Abstract: ***Biometrics plays an important role in recent security applications. Unimodal biometric systems can't perform well in certain applications due to the presence of noise in data collected by sensors. Moreover, inter-class similarities and intra-class variations may lead to misclassification. Multimodal biometric systems can be utilized to obtain promising identification ratios according to their higher accuracy. Multimodal systems not only improve performance but also reduce the problem of universality. In the present work, a feature level fusion technique that combines palmprint and iris images will be presented. The valley detection technique is used to extract the region of interest (RoI) of a palm. The neighbor-pixels value approach (NPVA) is used to extract the RoI of an iris. Discrete wavelets transform (DWT), Fast Fourier Transform (FFT), and discrete cosines transform (DCT) are used to extract discriminating features. Connectivity points and lifelines orientations are used to extract more palmprint features, whereas wavelet transform is used to obtain more iris features. A neural network classifier will be used for classification purpose in addition to a minimum distance classifier. The accuracy of the proposed system was 99.85 and % which exceeds the accuracy of 97.09 while using unimodal palmprint classification and that of iris which reached 96.83%.***

Keywords: Multimodal Biometric; Iris recognition; Palm-print recognition; feature level fusion

1. Introduction

The term "biometrics" indicates a pattern recognition technique that establishes a person's identity by extracting distinctive traits from his physiological and/or behavioral characteristics. Iris and palmprint are two physiological qualities noted for their persistence, uniqueness, and excellent identification accuracy among all attributes. Depending on whether a single modality or numerous modalities are used, biometric systems can be either unimodal or multimodal. Spoof attacks, low sample quality, intra-class variability, and user acceptability are all problems with unimodal biometric systems [1]. By merging information from many modalities, these issues can be avoided to a significant extent [2]. Every biometric system contains basic modules; data acquisition, RoI segmentation, feature extraction, matching and decision modules. Accordingly, data fusion levels can be classified into four categories; feature-level fusion, score-level fusion, decision-level fusion, and sensor-level fusion [3].

Sensor-level fusion combines data from many samples collected with the same sensor. Before storing data in a template, feature-level fusion entails combining different sets of features taken from the input image. The compatibility of many aspects is required for this kind of fusion to work. The scores acquired after applying different classifiers to the same or distinct collection of features are combined in score-level fusion. The final decision is made on the basis of the combined scores. Different classifiers' match/non-match decision is typically used to come up with a final decision in decision-level fusion. Rank-level fusion, on the other hand, combines the output of many biometric matchers to improve the matching system's reliability.

The present study aims to develop a biometric system by offering a feature representation approach that can extract significant features from both iris and palm-print images. The iris is a ring inside the eye that controls the amount of light that enters through the pupil. The radius of the iris increases and decreases depending on the amount of light that enters through the pupil. [4]. Between the wrist and the root-fingers on the human hand is the palm. Another advantage of using iris and palm-print is that they both have a high degree of uniqueness. They can also tell the difference between identical twins. Even a person's left and right iris (or palmprint) is not identical. Furthermore, both of these modalities are regarded to be stable across time. Following that, feature-level fusion is used to boost performance. The region of interest (RoI) is calculated using the sensor outputs (iris image and palmprint image). A gray-level co-occurrence matrix was used; feature vectors are taken from the processed image and merged to generate a single feature vector. Figure 1 shows a block diagram of a multimodal biometric system.

The paper is organized as follows; section 2 presents a literature review, section 3 presents the RoI segmentation techniques for both palmprint and iris, section 4 explains how feature extraction and fusion have been peformed, section 5 gives the experimental results, and finally section 6 gives the concluded remarks and future work.

2. Literature Review

A lot of work has been performed in the field of multi-modal biometrics. In [5], Hariprasath et al. suggested a feature-level fusion to combine the features collected from the iris and palmprint patterns into a 1408-bit multimodal pattern vector. The recognition rate was 94.50 percent in only 15.25 microseconds.

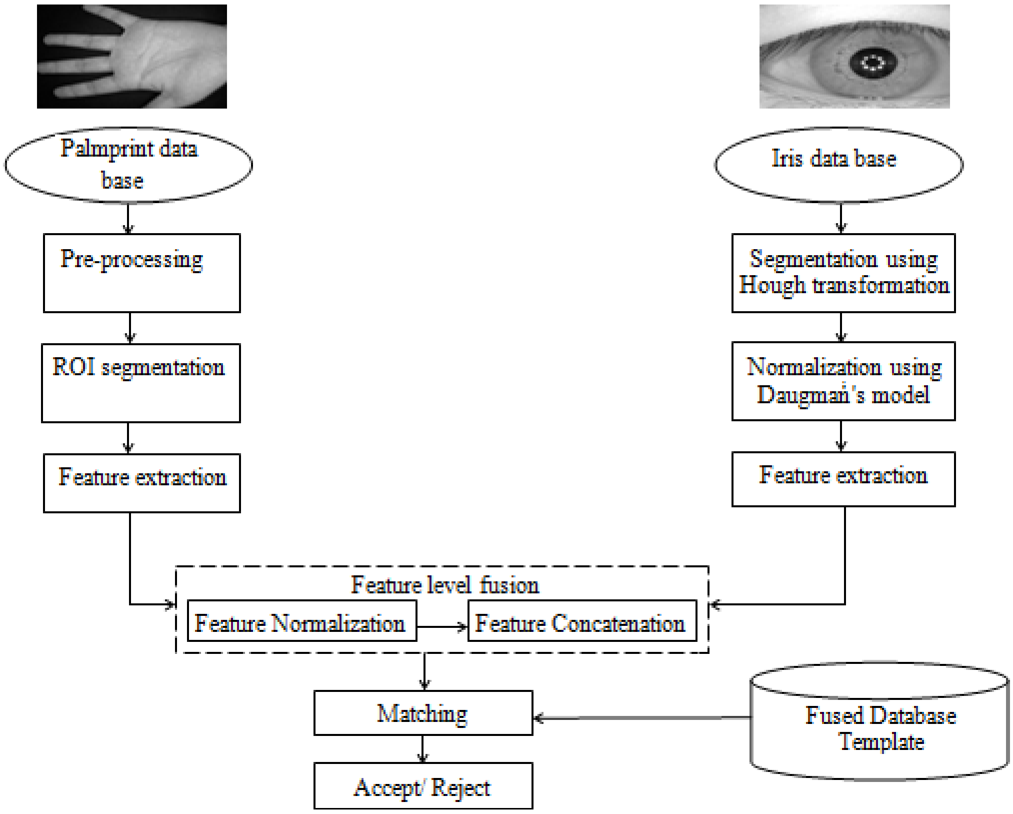


Figure 1: Block diagram of Feature level fusion System

Ritesh et al. [6] has presented a successful method known as bit-transition code. In the case of a multimodal biometric system, the procedure begins with a Gabor filter applied to the input images, which produces complicated replies. Following that, the imaginary and real components of the complex replies are concatenated and binarized together using zero-crossing. Gayathri et al. [7] have produced a palmprint and iris verification and identification technique based on wavelet-based feature level fusion. A wavelet-based feature fusion technique is utilized to fuse the extracted Gabor texture features. Wavelet extensions for feature reduction and a mean and max fusion rule to reduce correlation are used to assist this approach. The recognition accuracy of the multimodal biometric system was 99.2%, with a false rejection rate (FRR) of 1.6 percent. Ujwalla et al. [8] have suggested a strategy for feature level fusion and recognition using SVM, in which the fused features are trained independently using the Mahalanobis distance technique by SVM. In comparison to previous studies, there is an improvement in FAR, FRR, and response time performance. Nassima et al. [9] have proposed a simple and tailored method for feature extraction which was based on wavelet packet decomposition at four levels with simple binary coding this result in 256 packets that can be used to construct a compact binary code. It is calculated using the first three highest energy peaks to compute an adaptive threshold that allows each wavelet packet to be affected by 0 or 1. The results showed that decision-level fusion with t-Norm produced the greatest outcomes. Archana et al. [10] has presented a multi-biometric method that combines three traits: fingerprint, palmprint, and iris. The system creates a fusion at the matching score level, which is the quickest. The suggested system displays the results of three different qualities. These scores indicate how comparable the features are. The weighted fusion approach is used to integrate the scores. E. Sujatha et al. [11] have developed a multi biometric approach for image analysis and authentication based on encoded discrete wavelet transform that integrates iris, face, palm print, and signature. When compared to individual biometric features, Using a multimodal biometric method, it reduces memory size, improves recognition accuracy, and improves ERR. In L. Nisha et al. [12], the second order texture features were extracted using the gray level co-occurrence Matrix (GLCM) approach. These extracted features are fused at the feature level and then subjected to the Recognition procedure. When comparing sensitivity to accuracy and specificity, the Artificial Neural Network (ANN) with Particle Swarm Optimization (PSO) approach achieved a high sensitivity. In T. Vijayakumar et al. [13] a multimodal biometric model for user identification has been produced. For feature extraction, the system employs the CNN deep learning algorithm. To identify the person from the iris, face, finger vein, and palm print, feature level fusion and two distinct methods of score fusion were used. It allows for more precision when using a CNN and a finger vein support vector machine (SVM) to make palmprint images. Gayatri et al. [14]have developed a method for concatenating reduced dimension feature vectors for three biometric traits: face, palmprint, and ear. The system is more resilient since only one approach, Principal Component Analysis, was used for Euclidean distance and feature extraction was used for final matching.

3. RoI Segmentation

One of the most important aspects of any biometric system is the segmentation of the region of interest (RoI) from the recorded image. The segmentation precision has a direct bearing on the system's overall performance.

3.1 Iris segmentation

Before using the iris picture for feature extraction, it must first be preprocessed. Undesired details in the image, such eyelids, pupils, sclera, and eyelashes, should be removed. As a result, iris segmentation, iris normalization, and image enhancement must all be performed by the iris preprocessing module. Segmentation is a crucial module for removing non-essential data, such as the area outside the iris (eyelids, sclera, and skin) and pupil segment. The iris boundary is estimated. The canny algorithm is used to process the iris image first, which creates the edge map for the iris image, which is then used to estimate the boundary. Using Hough transformations, the edge map is used to detect the exact pupil and iris boundary [15]. Separating the eyelid and eyelashes is the next step. The eyelid edge information was extracted using image binarization and the horizontal segmentation operator. In the horizontal direction, the eyelids span the entire image. In the area where the eyelids meet, the average of vertical slopes is higher.

Demarking line for eyelids is the largest horizontal line feasible. This is used to divide it into two sections as a separator. The eyelid boundaries were simulated using parabolic curves based on the edge points identified. The polar image of the iris is translated into the Cartesian frame during normalization, resulting in a rectangular strip as shown in Fig.2. It is done using Daugman's rubber sheet model [16] which assigns a pair of polar coordinates (r, θ) to each point within the iris region, where r is on the interval [0, 1] and θ is the angle. Finally, image enhancement was achieved using histogram equalization. Fig.3 illustrates the detailed steps of iris segmentation.

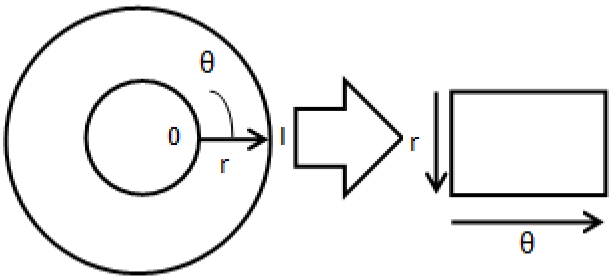


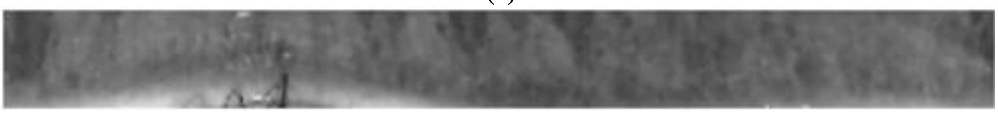
Figure 2: Daugman's rubber sheet model

3.2 Palmprint Segmentation

The palmprint region may be easily located by locating the finger-valley points and extracting the region that falls normal to the line connecting those valley points. The reference points are automatically extracted using a curvature scale space corner detector with an adaptive threshold and a dynamic supporting region [17]. The steps of the procedure are as follows:

1) Using the Canny edge detector, create a binary edge-map from the grey level image.
2) Fill in the gaps in the contours by extracting the edge contours from the edge-map.
3) For each contour, to maintain all true corners, compute curvature at a small scale. All of the curvature local maxima are initial corner candidates.
4) Initial corner candidates are compared using an adaptive local threshold to remove round corners.
5) Rounded corners and false corners caused by boundary noise and details are discarded, and all local maxima of curvature are considered corner candidates.
6) If the line mode curve's end points are not close to the corners detected above, they were added as corners

(a)



(b)

Figure 3: (a) Localized iris image and (b) Normalized iris image

The four finger-webs, five fingertips, and three additional hand reference points make up the final group of hand reference points. A line segment is drawn between the finger-web and the extra reference point between the index fingers and pinkie [18]. The vertices of the square RoI are formed by connecting the centre points of the line segments. For each input image, the generated square will be different sizes and orientations, thus they must be rotated to a vertical position and enlarged to a standard dimension. The smaller the size, the less computing effort is required for further processing, resulting in reduced processing time and memory usage. The proposed method was evaluated on 480 images collected from the CASIA database, eight for the left hand and eight for the right hand. All of the images yielded excellent segmentation with high accuracy. Figure 4 shows the results for both original palmprint images and segmented regions of interest.

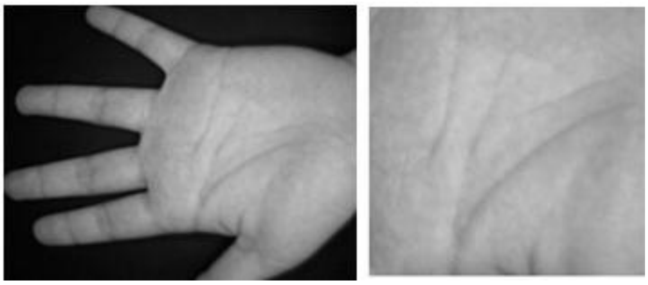


Figure 4: Example for palmprint images and resulting RoI's

4. Feature Extraction and Feature Fusion

A palmprint in a wavelet feature set can be described by feature extraction. A distinguishing trait should have a big variance across individuals and a small variation in samples from the same person. Transformation-based approaches are commonly utilized to employ palmprint textures as features. Wavelet Transform [19, 20, 21], Discrete Cosine transform [20, 22], and Fourier transform [19, 22] are examples for transformed features. The Fourier transformation allows for both reverse and forward spatial to frequency conversions, as well as frequency to spatial conversion. Detecting edge lines with a high pass filter and smoothing out the image with a low pass filter, it's used for image enhancement. However, except from the frequency domain, they do not supply any additional values for palmprint feature extraction. The Discrete Cosine Transformation (DCT) is a Fourier-related transform that operates on actual data and is nearly twice the length of the Fourier Transform. It is utilized in image processing for data compression and feature extraction. When a high number of characteristics are used for recognition, extracting them takes a long time, and the recognition rate gradually decreases. The wavelets in a discrete wavelet transform are discretely sampled. The wavelet transform is well suited to studying images in which components represent the majority of the information. The wavelet function aims to achieve a good balance between frequency and time domains. Wavelets are also good at extracting features, however choosing the right wavelet family and wavelet was a challenge. The textural properties of the palm and iris in this experiment were extracted using these techniques.

DWT Features

DWT (Discrete Wavelet Transform) is an image decomposition and feature extraction algorithm that is widely used. When the two-dimensional DWT is utilized on an image, high-pass and low-pass filters are used to subsample it into four subsampled images. The output of the low-pass filter is decomposed further, while the output of the high-pass filter is discarded. In general, subsampled images are referred to as LL, LH, HL, and HH. A mathematical notation for translating a function of time into a function of frequency is the Fast Fourier Transform. To remove the occlusion caused by eyelids and eyelashes, the iris image is divided. Following that, the picture's polar form is converted to Fourier form, and the Fourier co-efficient is used as a feature of each unique iris image. The following two-dimensional Cartesian function is used to describe the iris image:

$$f(x, y) = \sum_{n=0}^{Q} \sum_{m=0}^{Q} F\,(n.m)\ \varphi\,(x-n, y-m) \quad (1)$$

Where $\varphi(x, y) = \frac{\sin\pi x}{\pi x} . \frac{\sin\pi y}{\pi y}$ and Q is size of the image F (n, m) is grey level at pixel (n. m)

For feature extraction, the normalized iris image is used. The features of the iris image are computed using the first level energy (1) and the computed standard deviation (2) of each sub-band.

$$\text{Energy} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} |X(m,n)| \quad (2)$$

The energy of the discrete function X (m, n) is computed using equation (2)

$$\sigma_k = \frac{1}{MXN} \sum_{i=1}^{N} \sum_{j=1}^{N} E[W_k(i,j) - \mu_k] \quad (3)$$

Where $W_k(i, j)$ represents the K^{th}wavelet decomposed sub-band.

DCT Features

The Discrete Cosine Transform (DCT) is a finite series of data points expressed as the sum of cosine functions pulsing at various frequencies. The DCT coefficients are a reflection of the many frequency components found in it. The DCT coefficient in the first position relates to the signal's DC component, which has the lowest frequency and conveys the most relevant information in the input signal most of the time. The coefficients at the end indicate the higher frequencies, and they usually represent the original signal's finer characteristics. Additional levels of information from the input signal are carried by the remaining coefficients. To extract features, DCT is first applied to the complete normalized image. When DCT is applied to an image, The DCT spectrum's upper corner is where all of the low-frequency components gather. The iris' primary identifying features are represented by the low frequency components, while the finer details are represented by the high frequency components. In recognition-based applications, low frequency components are adequate, therefore the components in the top left corner of the spectrum are retrieved and the rest is discarded. The transition of an image from the spatial to the frequency domain is shown in Fig.5. DCT is applied to each block from top to bottom, from left to right. Each block is compressed by the use of quantization. The DCT coefficients are subsequently converted to binary, which are used to create image templates. For binary bits, Positive coefficients are assumed to have a value of one, whereas negative coefficients are ignored. The templates are compared using the same nominal size, orientation, position and illumination. All of the low to mid frequency DCT coefficients with the maximum variance are contained in the feature vector.

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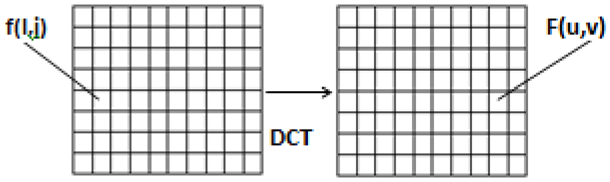

Figure 5: Transformation from spatial domain to frequency domain

FFT Features

A mathematical model for transforming a time function to a frequency function is known as the Fast Fourier Transform. DWT is used to obtain the wavelet coefficient from the time and space domain, while the frequency coefficient is computed using FFT, i.e. characteristics from the frequency domain. Because it takes less time to compute, the Fast Fourier transform is an enhanced version of the DFT [23]. Any image in the spatial domain is defined in terms of gray-scale value or intensity. As a result, each image channel is represented in its amplitude form using DFT, with amplitude values recorded in X and Y frequencies (i. e. frequency domain) (to extract the frequency features or components). FFT ignores the transparency and performs the DFT and inverse sequences. The FFT algorithm is a well-known feature extraction algorithm that avoids the property of replication, which FT cannot hold. As a result, FFT is used to rearrange the computation of FT components, resulting in a significant increase in speed. [24]. These parability property is applied into two steps: first, rows are transformed using 1D-FFT, and then columns are transformed using the same data. As a result of using the FFT, Each component's position indicates its frequency. Components with low frequency are centered. High frequency components are spread in the shape of edges. Mean, energy, variance, maximum and minimum amplitude, frequency (average, mid, maximum, and minimum), are among the extracted properties.

4.1 Feature-Level Fusion

For subsequent processing, this fusion primarily entails the fusion of feature vectors collected from several biometric features [25]. The new concatenated feature vector that was produced has more dimensions. Furthermore, feature reduction techniques could be used on a huge feature set to produce significant results. This feature extraction level fusion methodology is thought to outperform existing fusion methods [26]. Biometric template information is more detailed with feature level fusion. Prior to matching, feature level fusion is used to integrate biometric data. When compared to score level fusion, feature level fusion reduces response time. Feature level fusion is not widely used due to the difficulty of fusing incompatible feature vectors from several modalities. Concatenating the extracted features is the most basic form of this level of fusion.

The steps involved in feature fusion will be summarized in the following sub-sections.

4.1.1 Normalization of Feature Vector

Due to differences in range and distribution, the feature vectors derived independently from the iris and palmprint images have natural incompatibilities. One solution is to use a normalization approach to make the feature vectors normal (min-max, z-score, median). The min-max normalization approach is used in this case [27]. The feature vectors are normalized and can be represented using min-max normalization as in equation 4.

$$X\prime = \frac{xi - \min\ (X)}{\max(X) - \min\ (X)} \quad (4)$$

4.1.2 Fusing the Feature Vector

The final fused vector is obtained by simply concatenating the normalized feature vectors of the iris and palmprint regions into a single fused vector. Let Ei= {e1, e2, e3. . . en} and Ii= {i1, i2, i3. . . in} be the normalized feature vectors of iris and palmprint region. The fused vector (4) is represented as

$$Fused_{vector} = [e1, e2, e3... en\ i1, i2, i3... in] \quad (5)$$

5. Experimental results

The palm and iris datasets from the CASIA database [28, 2] were used in the experiments. The proposed method was tested on a sample of 800 images from 50 people, eight for the left side and eight for the right side of the palm and the corresponding iris images. The experiments were conducted using Neural Network toolbox in MATLAB with different hidden layers to achieve the best performance. At the first level iris and palm were tested to get the accuracy for each of them. At the second level, using the proposed model, iris and palmprint were integrated at the feature level and the overall performance of the system has increased showing an accuracy of 99.85%. Tables (1-3) show a performance comparison between the proposed multimodal fusion system and each individual using DCT, DWT and FFT.

Table 1: Palmprint performance

Method	*Hidden layer (10) Accuracy in (%)*	*Hidden layer (15) Accuracy in (%)*	*Hidden layer (20) Accuracy in (%)*
DCT	97.24	97.23	97.15
DWT	97.23	97.17	97.24
FFT	97.09	97.07	96.75

Table 2: Iris performance

Method	Hidden layer (10) Accuracy in (%)	Hidden layer (15) Accuracy in (%)	Hidden layer (20) Accuracy in (%)
DCT	97.09	97.04	96.83
DWT	97.18	98.27	99.89
FFT	97.09	97.19	96.60

Table 3: Performance for the proposed multimodal fusion system

Method	*Hidden layer (10) Accuracy in (%)*	*Hidden layer (15) Accuracy in (%)*	*Hidden layer (20) Accuracy in (%)*
DCT for iris and palm	96.99	97.25	97.14
DWT for iris and palm	97.23	99.85	99.81
FFT for iris and palm	96.99	97.13	96.52
DCT iris with FFT palm	97.15	97.03	97.20
DCT palm with FFT iris	97.02	97.19	96.59

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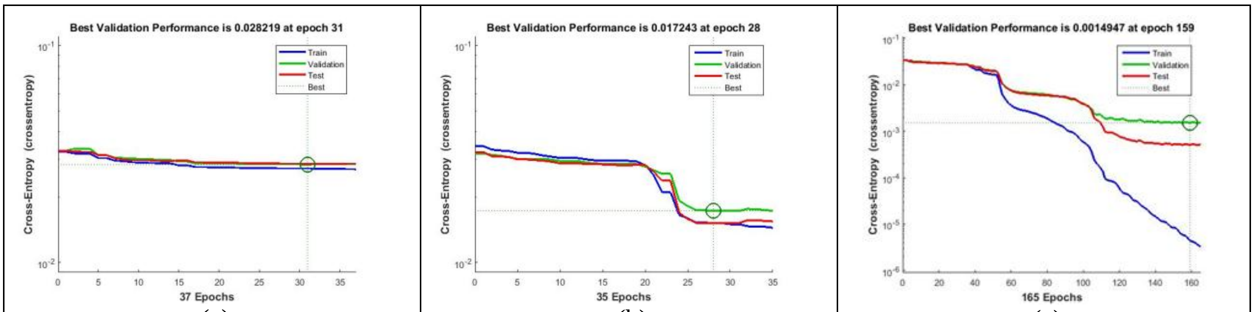

(a) (b) (c)

Figure 6: Performance curves (a) Palmprint (b) Iris (c) Fusion

6. Conclusions

In this paper, a multimodal biometric identification approach that combines iris and palmprint data is proposed. For palmprint and iris recognition, we described a transformation-based feature level fusion technique. The results of the experiments suggest that combining palmprint and iris features outperforms the use of a unimodal biometric. The suggested multimodal biometric system achieves 99.85 percent recognition accuracy. Future work will include more experimental tests using deep neural networks and other database sets.

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