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Human Verification using Multiple Fingerprint Texture Matchers

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Abstract

This paper presents a multimodal biometric verification system using multiple fingerprint matchers. The proposed verification system is based on multiple fingerprint matchers using Spatial Grey Level Dependence Method and Filterbank-based technique. The method independently extract fingerprint texture features to generate matching scores. These individual normalized scores are combined into a final score by the sum rule and the final score is eventually used to effect verification of a person as genuine or an imposter. The matching scores are used in two ways: in first case equal weights are assigned to each matching scores and in second case user specific weights are used. The proposed verification system has been tested on fingerprint database of FVC2002. The experimental results demonstrate that the proposed fusion strategy improves the overall accuracy of the system by reducing the total error rate of the system.

Keywords: - Multimodal biometric System, Fingerprint verification, SGLDM, Filterbank matching, Score level fusion, Sum rule.

1. Introduction

In today's wired information society when our everyday life is getting more and more computerized, automated security systems are getting more and more importance. The key task for an automated security system is to verify that the users are in fact who they claim to be. Traditionally password and ID cards have been used for human verification to restrict access to secure systems such as ATMs, computers and security installations [1]. The drawback with the traditional systems is that a password can be guessed or forgotten and similarly the ID card can be lost or stolen, thus rendering such methods of human verification unreliable. To overcome these problems, biometrics offers an alternative. Biometrics refers to identifying a person based on his or her physiological or behavioral traits. Face, fingerprints, hand geometry, iris, retina, signature, voice, facial thermogram, hand vein, gait, ear, odor, keystroke, etc. are some of the biometric features that are used for human verification and identification. Most of the biometric systems that are in use in practical application use a single piece of information for recognition and are as such called unimodal biometric systems. The unimodal biometric recognition systems, however, have to contend with a variety of problems like non-universality, susceptibility to spoofing, noise in sensed data, intra-class variations, inter-class similarities. Some limitations of the unimodal biometric systems can be alleviated by using multimodal system [2]. A biometric system that combines more than one sources of information for establishing human identity is called a multimodal biometric system. Combining the information cues from different biometric sources using an effective fusion scheme can significantly improve accuracy [3] of a biometric system.

The information fusion in multibiometrics can be done in different ways: fusion at the sensor level, feature extraction level, matching score level and decision level. Sensor level fusion is rarely used as fusion at this level requires that the data obtained from the different biometric sensors must be compatible, which is seldom the case. Fusion at the feature extraction level is not always possible as the feature sets used by different biometric modalities may either be inaccessible or incompatible. Fusion at the decision level is too rigid as only a limited amount of information is available. Fusion at the matching score level is, therefore, preferred due to presence of sufficient information content and the ease in accessing and combining match scores [4].

2. Related work

A number of works showing advantages of multimodal biometric verification systems have been reported in literature. Brunelli and Falavigna [2] have proposed personal identification system based on acoustic and visual features, where they use a HyperBF network as the best performing fusion module. Duc et al. [5] proposed a simple averaging technique combining face and speech information. Kittler et al. [6] have experimented with several fusion techniques using face and voice biometrics, including sum, product, minimum, median, and maximum rules and they have found that the best combination results are obtained for a simple sum rule. Hong and Jain [7] proposed a multimodal personal identification system which integrates face and fingerprints that complement each other. The fusion algorithm combines the scores from the different experts under statistically independence hypothesis. Ben-Yacoub et al. [8] proposed several fusion approaches, such as Support Vector Machines (SVM), tree classifiers and multi-layer perceptrons, combining face and voice biometrics. Pigeon at el. [9] proposed a multimodal person authentication approach based on simple fusion algorithms to combine the results coming from face, and voice biometrics. Choudhury et al. [10] proposed a multimodal person recognition using unconstrained audio and video and the combination of the two features is performed using a Bayes net. Jain at el. [11] combine face, fingerprint and hand geometry biometrics combining them under sum, decision tree and linear discriminant- based method. The sum rule is reperted to outperform others. Various other biometric combinations have been proposed [12, 13, 14] that report that combining more than one biometric modalities together result in improved performance than using them alone. Jhat et al. [15] have proposed a unimodal fingerprint biometrics verification system using texture feature of Energy of a fingerprint as a biometric trait that gives 70% Genuine Accept Rate (GAR) at 1% False Accept Rate (FAR) for effecting personal verification. To augment performance of the said proposed unimodal fingerprint verification system using a single matching score, in the present work, a multimodal biometric system based on multiple fingerprint matchers is proposed. The use of the proposed combination strategy in combining multiple matchers significantly improves the overall accuracy of the fingerprint based verification system by reducing the total error rates. We have chosen multiple fingerprint matchers as they form a good combination for a multimodal biometric system because the fusion of this combination in such systems demonstrates substantial improvement in recognition [3, 6]. It is due to the fact that the sources are fairly independent [16]. They not only address the problem of non-universality, since multiple traits ensure sufficient population coverage but also deter spoofing since it would be difficult for an imposter to spoof multiple biometric traits of a genuine user simultaneously. A multimodal biometric verification system based on multiple fingerprint matchers is, therefore, described in this paper. To construct the multimodal biometric verification system, we have combined two fingerprint matchers of Spatial Grey Level Dependence Method (SGLDM) [27] and Filterbank-based [19] for extracting matching scores. Such a system has, hitherto, not been tried in the reported literature. The rest of the paper is arranged as follows: Section 3 describes Fingerprint verification modules. Section 4 presents normalization of matching scores. Fusion of the normalized scores is addressed in section 5. Experimental results are shown in section 6 and section 7 concludes the paper.

3. Verification Modules

Fingerprint is the pattern of ridges and valleys on the tip of a finger and is used for personal verification of people. Fingerprint based recognition method because of its relatively outstanding features of universality, permanence, uniqueness, accuracy and low cost has made it most popular and reliable technique. Current fingerprint recognition techniques can be broadly classified as Minutiae-based, ridge feature-based, correlation-based [17] and gradient based [18]. The minutiae-based methods are widely used in fingerprint verification but do not utilize a significant component of the rich discriminatory information available in the ridge structures of the fingerprints. Further, minutiae-based methods have to contend with the problem of efficiently matching two fingerprint images containing different numbers of unregistered minutiae points. This is the due to these reasons that present work uses Texture- based representation of a fingerprint as the smooth flow pattern of ridges and valleys in a fingerprint can be also viewed as an oriented texture pattern [17].

Texture has been successfully used in extracting hidden information in medical images such as ultrasound [20], MRI [21], CT [22], retina [23] and Iris [24]. Although there is no strict definition of the image texture, however, being defined as a function of the spatial variation in pixel intensities (grey values), is useful in a variety of applications, e.g, recognition of image regions using texture properties [25]. Texture methods can be broadly categorized as: statistical, structural, modal, transform [25, 26]. Teceryan et al [25] and Matreka et al [26] present review of these methods.The two texture based matchers of Spatial Grey Level Dependence Method (SGLDM) and Filterbank-based, that are used in the present work for personal verification, are summarized as follows:

3.1 SGLDM- based Matching

Jhat et al. [15] have used Harlicks spatial grey level dependence matrix (SGLDM) [27] method for extracting statistical texture features. In SGLDM, second order joint conditional probability density function, $f(i, j|d, \theta)$ for directions θ = 0, 45, 90, 135, 180, 225, 270, and 315 degrees is estimated.

Each $f(i, j|d, \theta)$ is the probability of going from grey level i to grey level j, given that the inter-sample spacing is d and the direction is given by the angle θ. The estimated value for these probability density functions can thus be written in the matrix form:

$$\phi(d,\theta) = \left[f(i.j|d,\theta) \right] \tag{1}$$

Scanning of the image in four directions viz; θ = 0, 45, 90, 135 degrees is sufficient for computing these probability distribution function, as the probability density matrix for the rest of the directions can be computed from these four basic directions. This yields a square matrix of dimension equal to the number of intensity levels in the image for each distance d and direction θ. Due to the intensive nature of computations involved, often only the distances d= 1 and 2 pixels with angles θ = 0, 45, 90, 135 degrees are considered as suggested [26].

Let $\phi'(d,\theta)$ denote transpose of the matrix $\phi(d,\theta)$ for the intersampling spacing, d, and direction θ.

$$\begin{aligned} \phi(d,0) &= \phi'(d,180) \\ \phi(d,45) &= \phi'(d,225) \\ \phi(d,90) &= \phi'(d,270) \\ \phi(d,135) &= \phi'(d,315) \end{aligned} \tag{2}$$

The knowledge of $\phi(d,180), \phi(d,225), \phi(d,270), \phi(d,315)$, add nothing to the characterization of texture. If one chooses to ignore the distinction between opposite directions, then symmetric probability matrices can be employed and then the spatial grey level dependence matrices $S_o(d), S_{45}(d), S_{9o}(d), S_{135}(d)$, can be found from

$$S_o(d) = \frac{1}{2}[\phi(d,0) + \phi(d,180)] = \frac{1}{2}[\phi(d,0) + \phi'(d,0)] \quad (3)$$

Similarly $$S_{45}(d) = \frac{1}{2}[\phi(d,45) + \phi(d,225)] = \frac{1}{2}[\phi(d,45) + \phi'(d,45)]$$

(4)

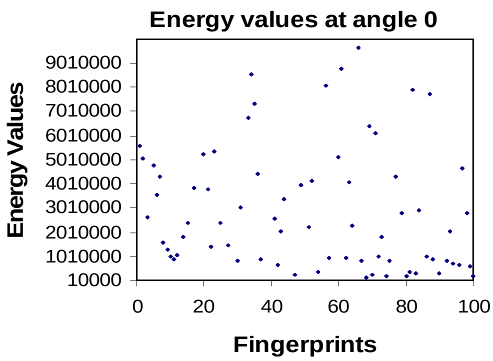
$S_{90}(d)$ *and* $S_{135}(d)$ can be similarly calculated.

Approximately two dozen co-occurrence features can be obtained using the above method and the consideration of the number of distance angle relations also will lead to a potentially large number of dependent features. Jhat et al. [15] have shown that the fingerprint texture feature of Energy can provide useful information for pattern recognition and can be used for verification. The Energy texture feature of a fingerprint is given by Equation 5.

$$E(S_\theta(d)) = \sum_{i=0}^{N_G-1} \sum_{j=0}^{N_G-1} \left[S_\theta(i,j|d)\right]^2 \quad (5)$$

Where $S_\theta(i, j|d)$ is the (i, j) th element of $S_\theta(d)$ and N_G is the number of grey levels in the image from which the spatial grey level dependence matrices are extracted.

The texture feature of Energy of the fingerprint is calculated using algorithm of SGLDM by taking d=1 [26], for different values of θ, for a fingerprint being a soft texture [17] require small values of d. The results of Energy values for the angle of 0, 45, 90 and 135 degrees are obtained as shown in Figure 1 and are used for discrimination of individuals and effecting personal verification. If the Euclidean distance between two Energy values of query and gallery fingerprint image is less than a threshold, then the decision that the two images belong to same finger is made, alternately a decision that they belong to different fingers is made.



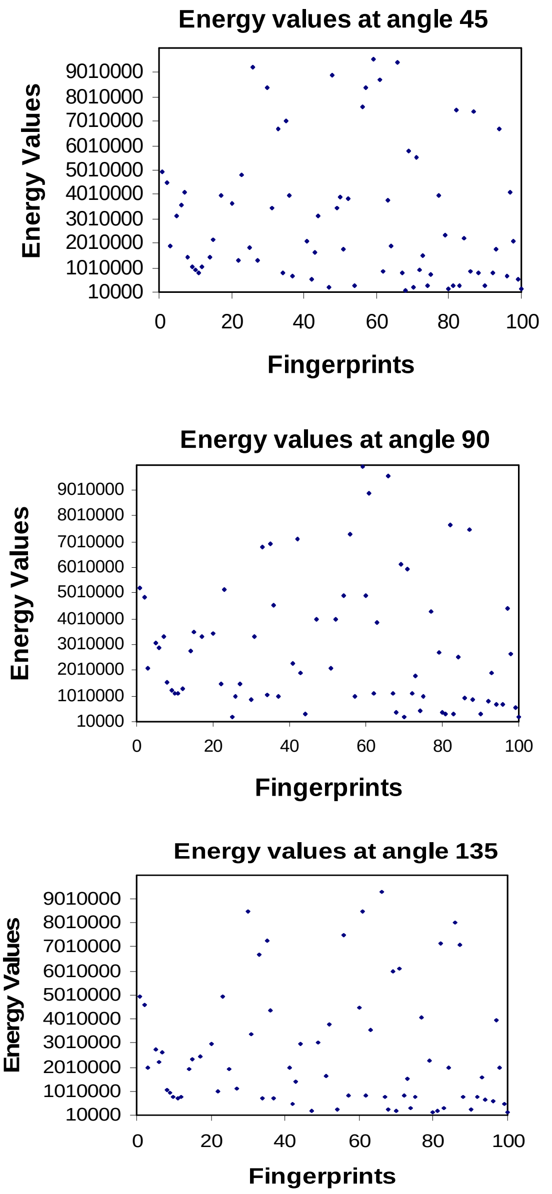


Figure 1. Energy Values for the angles of 0, 45, 90 and 135 degrees.

3.2 Filterbank-based Matching

Jain et al. [19] have proposed a fingerprint representation scheme that utilizes both global and local features in a compact fixed length feature vector called 'FingerCode'. The proposed scheme makes use of the texture features available in a fingerprint to compute the feature vector. In the Filter-based matching, generic representation of oriented texture relies on extracting a core point in the fingerprint which is defined as the point of maximum curvature of the ridge in a fingerprint. Then a circular region around the core point is located and tessellated into sectors. The pixel intensities in each sector are normalized to a constant mean and variance and filtered using a bank of 8 Gabor filters to produce a set of 8 filtered images. Grayscale variance within a sector quantifies the underlying ridge structures and is used as a feature. A feature vector termed as a FingerCode, is the collection of all the features, computed from all the sectors, in every filtered image. The FingerCode captures the local information, and the ordered enumeration of the tessellation captures the invariant global relationships among the local patterns. The matching stage simply computes the Euclidean distance between the two corresponding FingerCode values. Figure 2 depicts diagrammatic representation of the Filterbank matching algorithm as proposed by Jain et al. [19].

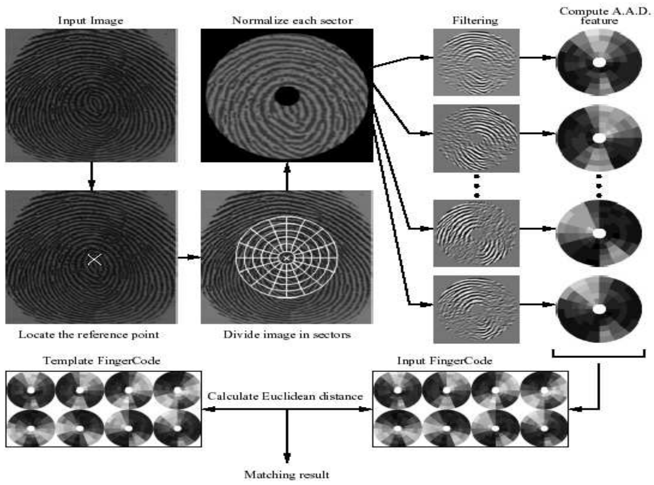


Figure 2. Diagrammatic representation of Filterbank Matching algorithm.

The first two steps of determining a center point for the fingerprint image and tessellate the region around the center point are straightforward. The filtering process and obtaining of feature vector can be summarized as follows:

3.2.1 Filtering

Let $I(x,y)$ denote the gray value at pixel (x,y) in an $M\times N$ fingerprint image and let M_i and V_i, the estimated mean and variance of sector S_i, respectively, and $N_i(x,y)$, the normalized gray-level value at pixel (x,y). For all the pixels in sectorS_i, the normalized image is defined as:

$$N_i(x,y) = \begin{cases} M_O + \sqrt{\dfrac{V_0 \times (I(x,y)-M_i)^2)}{V_i}}, & \text{if } I(x,y) > M_i \\ M_O - \sqrt{\dfrac{V_0 \times (I(x,y)-M_i)^2)}{V_i}}, & \text{otherwise} \end{cases} \quad (6)$$

Where M_0 and V_0 are the desired mean and variance values, respectively. The values of both M_0 and V_0 have been set to 100.

An even symmetric Gabor filter has the following general form in the spatial domain:

$$G(x,y;f,\Theta) = \exp\left\{\frac{-1}{2}\left[\frac{x'^2}{\delta_{x'}^2} + \frac{y'^2}{\delta_{y'}^2}\right]\right\}\cos(2\pi f x') \quad (7)$$

$$x' = x\sin\Theta + y\cos\Theta \tag{8}$$

$$y' = x\cos\Theta - y\sin\Theta \tag{9}$$

Where f is the frequency of the sinusoidal plane wave along the direction Θ from the x-axis, and $\delta_{x'}$ and $\delta_{y'}$ are the space constants of the Gaussian envelope along x' and y' axes, respectively. Let H indicate the enhanced image. Convolving H with eight Gabor filters in the spatial domain would be a computationally intensive operation. To speed up this operation the convolution is performed in the frequency domain. Let F(H) denote the discrete Fourier transform of H, and $F(G_\Theta)$ indicate the discrete Fourier transform of the Gabor filter having the spatial orientation Θ. Then the Gabor filter image, V_Θ, may be obtained as,

$$V_\Theta = F^{-1}\ [F(H)F(G_\Theta)] \tag{10}$$

Where F^{-1} is the inverse Fourier transform. Eight filtered images are obtained in this way.

3.2.2 Feature vector

The standard deviation within the sectors, in the filter-bank algorithm,, define the feature vector. Let $C_{i\Theta}(x,y)$ be the component image corresponding to Θ for sector S_i. For $\forall$ i ,i=0,1……………….,47 (as total of 48 sectors from S_0 to S_{47} are defined in six concentric bands around the central point) and Θ ϵ [0^0, 45^0, 90^0, 135^0] (as a fingerprint image is decomposed into four components images corresponding to four different values of Θ as mentioned). A feature is standard deviation $F_{i\Theta}$, which is defined as :

$$F_{i\Theta} = \sqrt{\sum_{k_i}(C_{i\theta}(x,y) - M_{i\theta})^2} \tag{11}$$

Where K_i is the number of pixels in S_i and $M_{i\Theta}$ is the mean of the pixel values in $C_{i\Theta}(x,y)$ in sector S_i. The average absolute deviations of each sector in each of the eight filtered image define the components of the feature vector called FingerCode. Fingerprint matching is then based on finding the Euclidean distance between the corresponding FingerCodes.

4. Normalization.

Normalization involves transforming the raw scores of different modalities to a common domain using a mapping function. In our case, both the matching scores are distance scores, yet they have different numerical range. To transform these numerically incompatible matching scores into a common domain prior to fusion, normalization is needed. Comparing different normalization techniques on different multimodal biometric systems, Ribaric at el. [28] conclude that no single normalization technique performs best for all systems. We have, therefore, used min-max technique. This technique is not only simple but best suited for the case where maximum and minimum values of the scores produced by the matcher are known. Besides, minimum and maximum scores can be easily shifted to 0 and 1 respectively. The matching scores are normalized using min-max technique as follows.

Let G represent the gallery templates, Q represent the query samples, and S_{qg} represent the match score of the particular query 'q',qϵQ with gallery template 'g', gϵG. Then S_{qG} represents the vector of scores obtained when a query 'q' is matched against the entire gallery G. In min-max normalization, the minimum and the maximum of this score vector are used to obtain the normalization score S'_{qg} as per Equation12. The normalized score lie in the range 0-1.

$$S'_{qg} = \frac{S_{qg} - \min(S_{qG})}{\max(S_{qG}) - \min(S_P G)} \qquad (12)$$

5. Fusion.

The matching scores, next to feature vectors, output by matchers contain the richest information [4] about the input pattern. Further, it is relatively easy to access and combine the scores generated by the different matchers. Consequently, integration of information at the matching score level is the most common approach in the multimodal biometric systems. The proposed method, therefore, fuses the individual match scores of the fingerprint and the fused score is used for verification. There are several classifiers for the fusion and analysis of several classifier rules is given in [6, 11]. It is suggested that the weighted sum rule is more effective and outperforms other fusion strategies based on empirical observations [29]. The weighted sum rule is defined as $S_{fusion} = \sum_{i=1}^{N} W_i S_i$ Where S_i is the normalized matching score provided by the i^{th} trait and W_i is the weight assigned to the i^{th} trait. The identity of a person is verified if $S_{fusion} \geq \eta, where\ \eta$ is the matching threshold. The weighting of the matching scores has been done in the following ways:

5.1 Weighing Matching Scores Equally

In the first experiment, equal weightage is given to two matching scores of a fingerprint and a new score is obtained. Then the final matching score $S_{fusion} = \sum_{i=1}^{2} \frac{1}{2} S_i$ is compared against a certain threshold value to make a decision for a person being genuine or an imposter. The Figure 3a shows the improved matching performance when equal weightage is given to both matching scores of the fingerprint.

5.2 Weighing Matching Scores Unequally

When biometric trait of a user cannot be reliably acquired, the user will experience high false reject rate. This can result when the biometric trait becomes unreadable due to dirty or worn down dry fingers. In such a situation, the false error rate can be reduced and accuracy improved if different matching scores are weighted differently for increasing the influence of one or the other matching score as per degree of importance for different users. Weights indicate the importance of individual biometric matchers in a multibiometric system and, therefore, the set of weights are determined for a specific user such that the total error rates corresponding to that user can be minimized. User specific weights are estimated [29] from the training data as follows:

1. For the i^{th} user in the database, vary weights $W_{1,i}$, *and* $W_{2,i}$ over the range [0,1], with the condition $W_{1,i} + W_{2,i} = 1$
2. Compute $S_{fusion} = W_{1,i} S_1 + W_{2,i} S_2$
3. Choose that set of weights that minimizes the total error rate associated with the scores. The total error rate is sum of the false accept and false reject rates.

The user specific weight procedure utilizes the histograms of both the genuine and imposter score and computing user-specific thresholds using imposter scores have been shown not to improve performance [30] very much. In the second experiment, with a common threshold, therefore, we assign different weights to matching scores to minimize false accept rate and false reject rate associated with an individual and improve further the matching performance. The improved matching performance when user specific weights are used, is shown in Figure 3b.

6. Experimental Results

The suggested method has been tested on fingerprint databases of FVC2002 DB1 and DB2 [31]. Both the databases contain images of 110 different fingers with 8 impressions for each finger yielding a total of 880 fingerprints in each database. The databases has been divided into two sets: A and B. Set A contains the fingerprint images from the first 100 fingers as evaluation set and Set B contains the remaining 10 fingers as a training set. About 10 fingerprint images were eliminated from the database as Filter-based matcher rejected the images either being of poor quality or failing to locate the center. The False Accept Rate (FAR) and False Reject Rate (FRR) for the suggested method were evaluated by using the protocols of FVC2002 [32]. Each fingerprint impression in the subset A is matched against the remaining impressions of the same finger to compute genuine distribution. The total genuine attempts is (8×7)/2×90 = 2520. For Imposter distribution, the first fingerprint impression of each finger in subset A is matched against the first impression of the remaining fingers. The total imposter attempts is (90×89)/2 = 4005. The normalized genuine and imposter distribution matching scores for DB1 and DB2 are shown in Figures 4(a) and (b) respectively.

For the multiple matcher combination, we randomly selected each of the genuine and imposter scores for the training and remaining each half for the test. This process has been repeated 5 times to give 5 different training sets and 5 corresponding independent test sets. For authentication, we randomly selected four impressions of each fingerprint and enrolled them as templates into the system database. The remaining 90 × 4 = 360 fingerprints images in each database were used as input fingerprints to test the performance of our proposed method. The matching scores of the two classifiers are then summed and the final matching score is compared against a certain threshold value to recognize the person as genuine or an imposter. The FAR and FFR rates with different threshold values were obtained based on 90 × 360 = 32400 matches in each database.

False Accept Rate FAR (%)	False Reject Rate FRR (%)		
	SGLDM	Filter	SGLDM +Filter
1	19.8	15.3	4.9
.1	34.5	26.0	13.8
.01	39.4	32.1	17.3

Table 1. False Reject Rates (FRR) with different values of False accept rates (FAR) when matching scores are equally weighted.

False Accept Rate FAR (%)	False Reject Rate FRR (%)		
	SGLDM	Filter	SGLDM +Filter
1	18.2	14.5	3.8
.1	33.2	24.9	12.7
.01	37.8	30.9	15.5

Table 2. False Reject Rates (FRR) with different values of False accept rates (FAR) when matching scores are unequally weighted.

To demonstrate the effectiveness of the proposed method, tables showing FAR and FRR are drawn in Table 1 and Table 2. Besides, ROC curves between FAR and GAR have also been plotted in Figure 3a and Figure 3b. It is evident from the ROC curves that performance gain obtained for the proposed fusion system is higher as compared to the performance obtained for two individual matchers. As shown in the Figures 3a and 3b, the integration of matchers enhances the performance of the proposed multimodal verification system over the unimodal fingerprint matcher as proposed in [15] by giving Genuine Accept Rate (GAR) of 95.1% and 96.2% respectively at False Accept Rate (FAR) of 1%.

7. Conclusion

A biometric verification system using a single fingerprint texture matcher is less accurate for effecting personal verification. To enhance the performance of such a unimodal verification system, a multimodal biometric verification system using multiple fingerprint matchers is proposed. The proposed verification system use Spatial Grey Level Dependence Method (SGLDM) and Filterbank-based matching technique to independently extract fingerprint texture features to generate matching scores. These individual normalized scores are combined into a final score by the sum rule. The matching scores are used in two ways, in first case equal weights are assigned to each matching scores and in second case user specific weights are used. The final fused score is eventually used to conclude a person as genuine or an imposter. The proposed verification system has been tested on fingerprint database of FVC2002. The experimental results demonstrate that the proposed fusion strategy improves the overall accuracy of the of the unimodal biometric verification system by reducing the total error rate of the system.

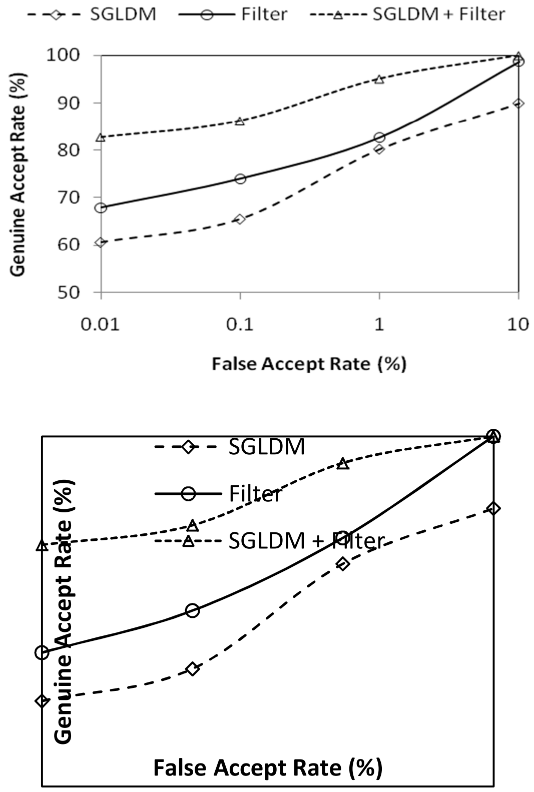
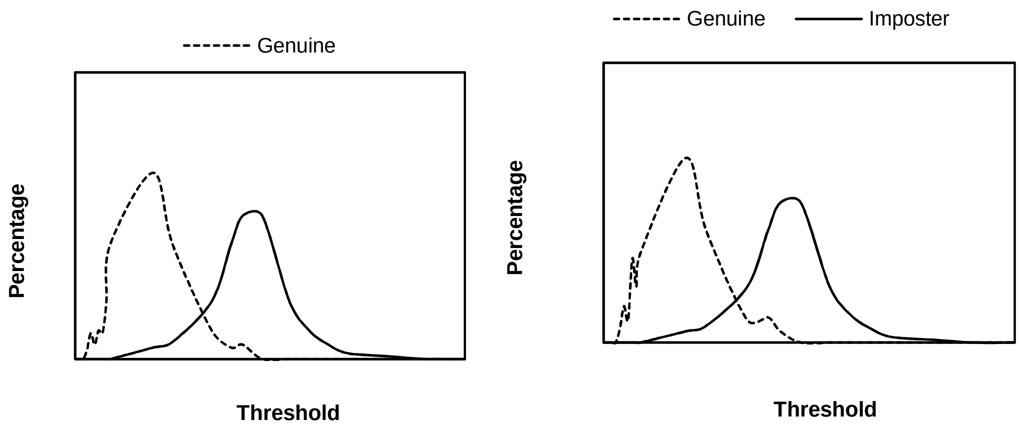


Figure 3. ROC curves showing performance improvement of combination of matchers over individual matchers when matching scores are (a) weighted equally (b) weighted unequally.



(a) **(b)**

Figure 4. Genuine and Imposter distributions for (a) DB1, (b) DB2.

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