Personal Verification using Fingerprint Texture Feature

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Abstract

Fingerprint is a reliable biometric which is used for personal verification. Current fingerprint verification techniques can be broadly classified as Minutiae-based, ridge feature-based, correlation-based and gradient-based. In this paper, we propose use of the statistical texture analysis of a fingerprint using spatial grey level dependence method (SGLDM) for discrimination and personal verification. This method extracts texture features by an algorithm based on the spatial grey level dependence method. The fingerprint images were chosen from DB1 and DB2 fingerprint databases of FVC 2002. Results show that fingerprint texture feature can be reasonably used for discrimination and for personal verification.

Keywords:--*Biometrics; fingerprint; texture; verification; spatial grey level dependence method.*

1. Introduction

Human identification is the association of an identity with a human being. Traditionally, password and ID cards have been used for identification to restrict access to secure systems but these methods can be easily breached, for password can be guessed and ID card can be stolen, thus rendering them unreliable [1]. Biometrics, which refers to identifying a person based on his or her physiological or behavioral characteristics, has the capability to reliably distinguish between an authorized person and an imposter [2]. In biometrics, identity of a person can be resolved in two ways: verification and identification. In the former a person to be identified submits a claim; which is either accepted or rejected. In the latter, a person is identified without a person claiming to be identified. In literature verification and identification are interchangeably used for biometrics recognition. In the present work we shall be concerned with biometrics verification only. Among all the biometrics, e.g, face, fingerprints, hand geometry, iris, retina, signature, voice, facial thermogram, hand vein, gait, ear, odor, keystroke, etc. [3], fingerprint based recognition method because of its relatively outstanding features of universality, permanence, uniqueness, accuracy and low cost [4] has made it most popular and reliable technique. As the process of personal identification continues to grow in sophistication, fingerprinting remains the best method to establish personal verification [5].

The reminder of the paper is organized as follows: Section 2 briefly summarizes the related work. Section 3 presents the method used to extract texture features. Section 4 gives implementation and results obtained. Comparison is given in Section 5. Section 6 presents discussion. Section 7 concludes the paper.

2. Related Works

Fingerprint is the pattern of ridges and valleys on the tip of a finger and is used for personal verification of people [6]. Henry Fauld in 1880 laid the scientific foundation of the modern fingerprint recognition by introducing minutiae feature for fingerprint matching [6]. Most automatic fingerprint identification systems employ techniques based on minutiae points. A minutiae represents local discontinuities and mark position where the ridge comes to an end or bifurcates in to two. Given a pair of fingerprints and their corresponding minutiae features, the process of matching can be treated as a point pattern matching problem and counting total number of matched minutiae. The minutiae-based methods require accurate detection of the minutiae from a fingerprint image. Although the minutiae pattern of each finger is quite unique, noise and distortion during the acquisition of the fingerprint and errors in the minutiae extraction process result in a number of missing and spurious minutiae [7]. To overcome the difficulty of reliably obtaining minutiae points from a poor quality fingerprint image, ridge feature-based method is used. A ridge is pattern of lines on a finger tip. This method uses ridge features like the orientation and the frequency of ridges, ridge shape and texture information for fingerprint matching. However, the ridge feature-based methods suffer from their low discrimination capability [6]. The correlation-based techniques make two fingerprint images superimposed and do correlation (at the intensity level) between the corresponding pixels for different alignments. These techniques are highly sensitive to non-linear distortion, skin condition, different finger pressure and alignment [8]. Most of these techniques use minutiae for alignment first.

The smooth flow pattern of ridges and valleys in a fingerprint can be also viewed as an oriented texture [4]. Jain and others describe a global texture descriptor called 'Finger Code' that utilizes both global and local ridge descriptions [10] for an oriented texture such as fingerprints. 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. The disadvantage of 'FingerCode' approach is that it requires that core be accurately located. This is a difficult problem in itself. A variation to this method is used by Chikkerur et al [7] that use localized texture features of minutiae and another one by Zhengyu et al [9] that uses texture correlation matching. Further, Aggarwal et al [11] propose gradient based approach to capture textural information by dividing each minutiae neighborhood locations into several local regions of which histograms of oriented gradients are then computed to characterize textural information around each minutiae location.

None of the methods in vogue today for fingerprint discrimination and personal verification use statistical texture analysis of a fingerprint using spatial grey level dependence method (SGLDM). In this paper, we suggest a method of discrimination and personal verification based on the statistical texture features of a fingerprint, for this is a most popular method [12]. Texture has been successfully used in extracting hidden information in medical images such as ultrasound [13], MRI [14], CT [15] and retina [16]. Besides Iris [17] texture method has also been used for human recognition. Statistical texture method using spatial grey level dependence method (SGLDM) has not been used hitherto by using fingerprint as a biometric. 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 [12]. Texture methods can be broadly categorized as: statistical, structural, modal, transform [12, 18]. Teceryan et al [12] and Matreka et al [18] present review of these methods. We have not used structural method as structural features may not be visibly perceptible; modal method is also avoided as we don't know which parameters control the useful feature vector and so is transform method avoided as it is time consuming.

3. Texture Feature Extraction Using SGLDM

Haralick [19] spatial grey level dependence matrix (SGLDM) is one of the most popular methods 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 [18].

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

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

Similarly

$$S_{45}(d) = \frac{1}{2}[\phi(d,45) + \phi(d,225)] = \frac{1}{2}[\phi(d,45) + \phi'(d,45)] \tag{4}$$

$S_{9o}(d)$ *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. In the present work we restrict representation to four features of Energy, Entropy, Local Homogeneity and Inertia, which can provide useful information for pattern recognition, though we could use more without gain or loss of information. Texture features of Energy, Entropy, Local Homogeneity and Inertia are given as follows:

a. E: ENERGY

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

b. H: ENTROPY

$$H\left(S_\theta(d)\right)=\sum_{i=0}^{N_G-1}\sum_{j=0}^{N_G-1}\left[S_\theta(i,j|d)\right].\log S_\theta(i,j|d) \tag{6}$$

c. L: LOCAL HOMOGENEITY

$$L\left(S_\theta(d)\right)=\sum_{i=0}^{N_G-1}\sum_{j=0}^{N_G-1}\frac{1}{1+(i-j)^2}S_\theta(i,j|d) \tag{7}$$

d. I: INERTIA

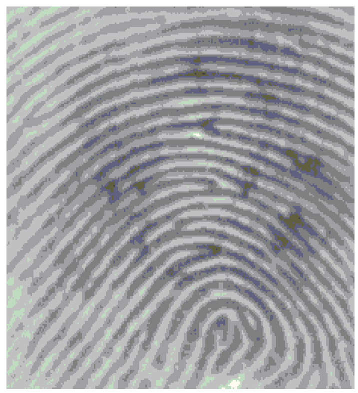
$$I\left(S_\theta(d)\right)=\sum_{i=0}^{N_G-1}\sum_{j=0}^{N_G-1}(i-j)^2 S_\theta(i,j|d) \tag{8}$$

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.

4. Implementation and Results

The fingerprint images were taken from DB1 and DB2 fingerprint databases of FVC2002 [20]. The fingerprints were downloaded on Core2 DUO, 2.53GHz with a 2GB RAM. The images were then converted into 256 color bitmap, each having a size of 235×260. Fig. 1(a) shows an actual fingerprint chosen randomly from the said database and Fig 1(b) shows its 256 color bitmap representation. The texture features of the converted bitmap fingerprint were calculated using an algorithm based on the SGLDM developed in the C language for it supports many low level features, being a mid level language.

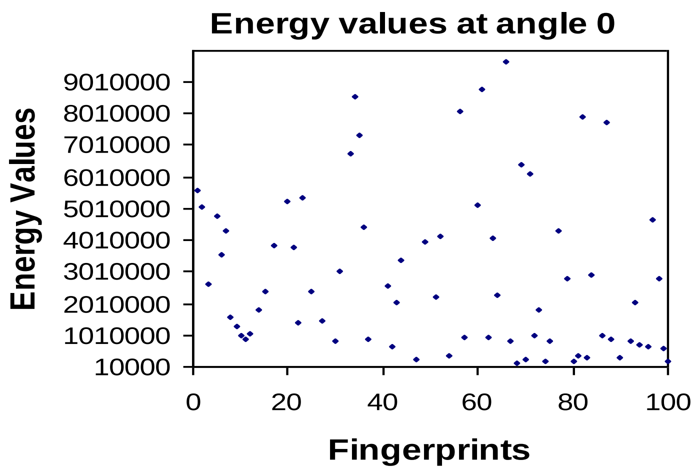
(a)

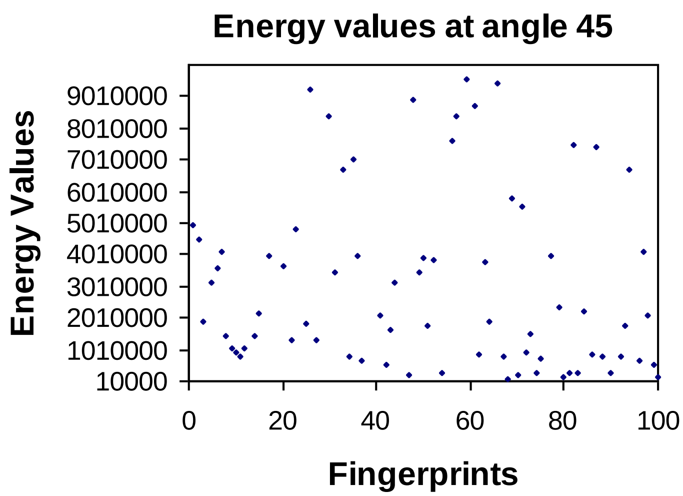


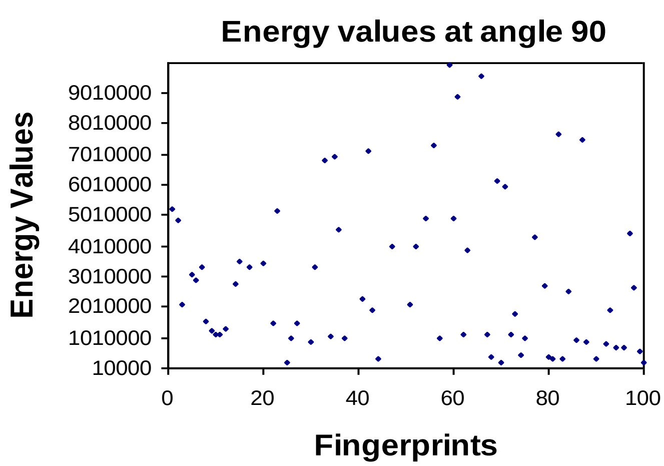
(b)

Figure 1: (a) Actual Fingerprint of FVC 2002, (b) 256 Colour Bitmap Representation.

We have chosen d=1 [18], for different values of θ, for a fingerprint being a soft texture [10] require small values of d, while as coarse textures require large values of d [18]. The results of Energy values for the angle of 0, 45, 90 and 135 degrees are shown in Fig. 2 for some of the images chosen from the said database using the above mentioned algorithm developed for extracting the texture features. It is obvious from the diagrams that the texture feature of Energy remains appreciably distinct for all the values of θ by a certain distinct margin. The values of Entropy and Local Homogeneity for the angles of 0, 45, 90, and 135 degrees for some of the fingerprints chosen randomly from the said databases have been found to remain almost same. The feature of Inertia though changes but for certain values of θ remains almost same as shown in Fig. 3. It is only the texture feature of Energy that remains appreciably distinct for all the values of θ by a certain distinct margin while same is not true for Entropy, Local Homogeneity and Inertia. The Energy texture feature of a fingerprint for the angles of 0, 45, 90, and 135 degrees, therefore, can be used for discrimination of individuals and effecting personal verification.


Energy values at angle 0
Energy Values
9010000
8010000
7010000
6010000
5010000
4010000
3010000
2010000
1010000
10000
0
20
40
60
80
100
Fingerprints


Energy values at angle 45
Energy Values
9010000
8010000
7010000
6010000
5010000
4010000
3010000
2010000
1010000
10000
0
20
40
60
80
100
Fingerprints


Energy values at angle 90
Energy Values
9010000
8010000
7010000
6010000
5010000
4010000
3010000
2010000
1010000
10000
0
20
40
60
80
100
Fingerprints

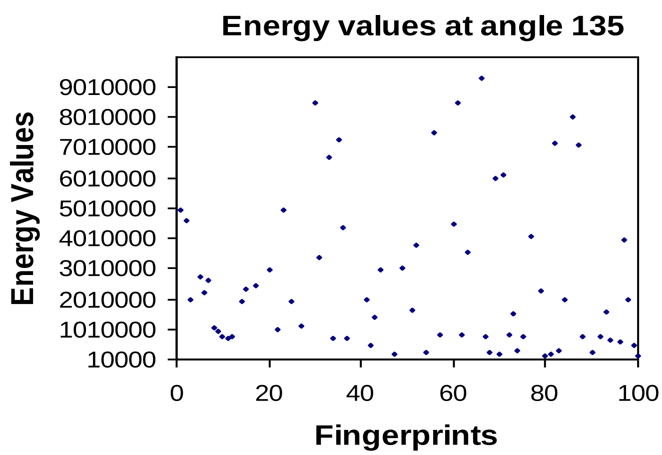
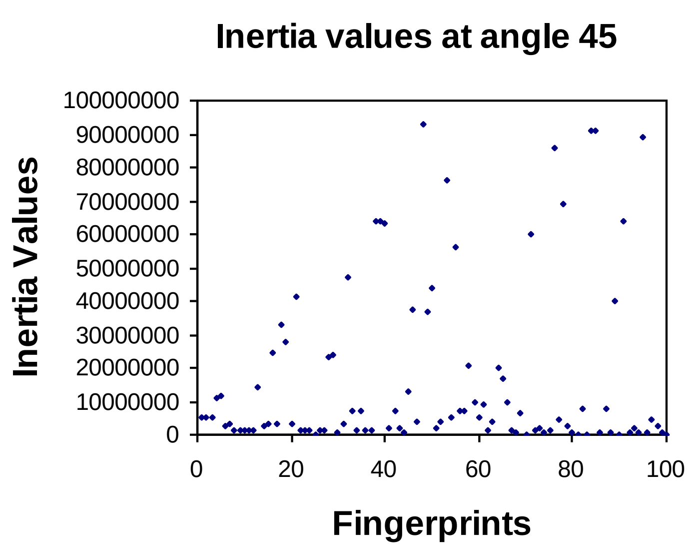


Figure 2: Energy Values for the Angles of 0, 45, 90 and 135 Degrees.

Our proposed method has been tested on fingerprint databases of FVC2002 DB1 and DB2 [20]. Both the databases contain images of 110 different fingers with 8 impressions for each finger yielding a total of 880 fingerprints in each database. Both the databases were captured by low and high quality optical sensors. The untrained volunteers were asked to give impressions of forefinger and middle finger of both the hands and were randomly partitioned into different groups; each group was associated to a DB and to different fingerprint sensor. The fingerprints, therefore, range from high quality to very low quality. In DB1, image size is 388×374 at 500 dpi; while as image size in DB2 is 296×560 at 569 dpi. Each database 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.



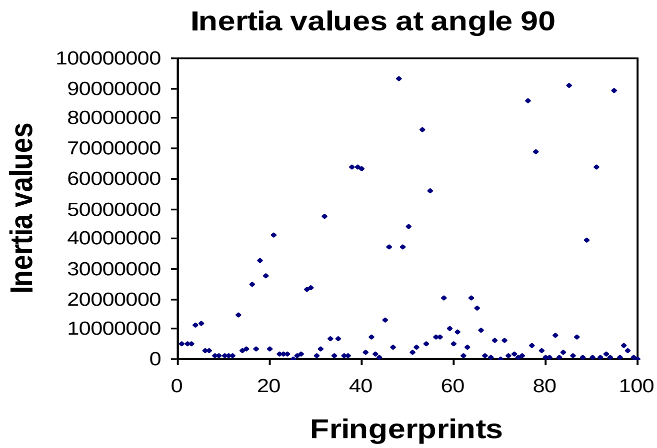


Figure 3: Inertial Values for the Angles 45 and 90 Degree.

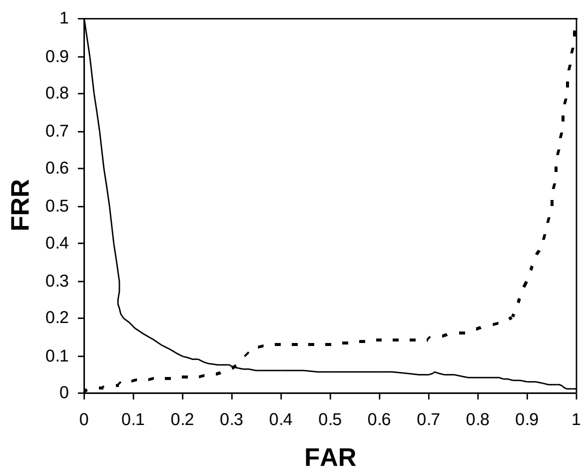
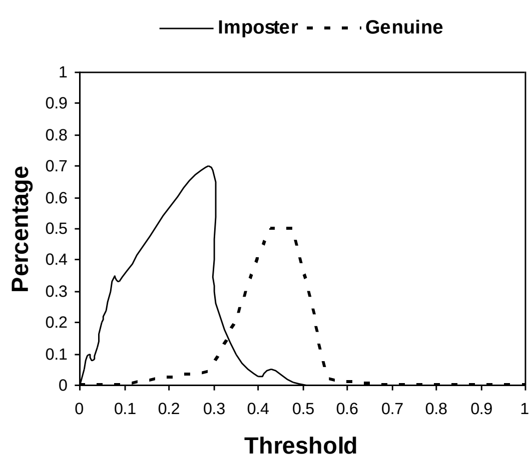
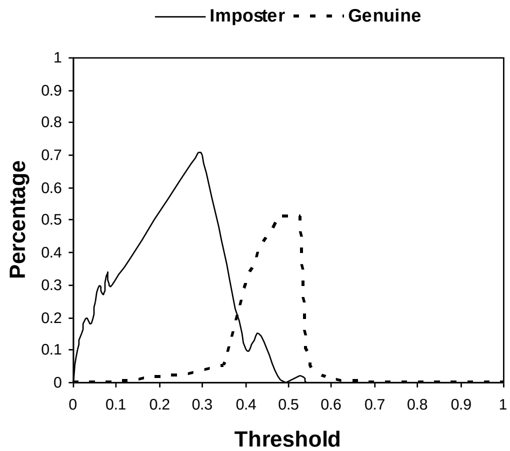


Figure 4: ROC Plot for DB1.



(a)



(b)

Figure 5: Genuine and Imposter Distributions for (a) DB1, (b) DB2.

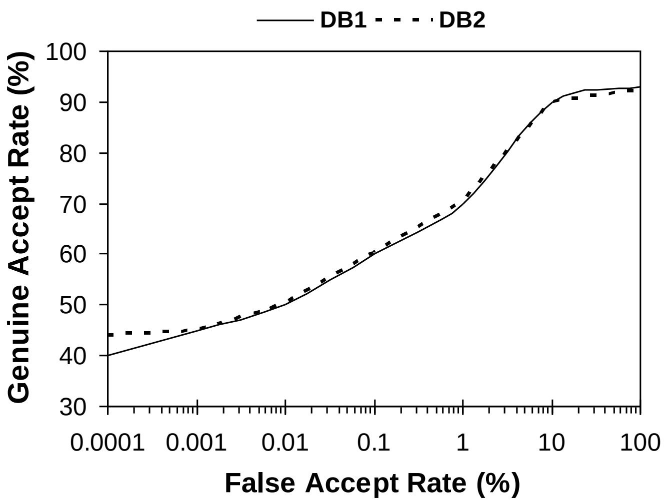


Figure 6: ROC Curves for Different Matchers for DB1 and DB2.

The protocols of FVC2002 [21] were followed to evaluate the False Accept Rate (FAR) and False Reject Rate (FRR) for the proposed method. For most fingerprint matching systems, these rates can be controlled by a parameter called threshold value. The Receiving Operating Curve (ROC), of which an example for DB1 is shown in Fig 4 is a plot in which FAR is plotted against FRR for different threshold values. The closer the curve approaches the point where FAR = 0 and FRR = 0, the better is the performance of the system. The threshold value where FAR= FRR is called the Equal Error Rate (ERR).

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 (with no rejects) is $(8\times7)/2\times100 = 2800$. 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 (with no rejects) is $(100\times99)/2 = 4950$. The normalized genuine and imposter distribution matching scores for DB1 and DB2 are shown in Figs. 5(a) and 5(b).

For authentication, we randomly selected four impressions of each fingerprint and enrolled them as templates into the system database. The remaining 100 × 4 = 400 fingerprints images in each database were used as input fingerprints to test the performance of our proposed method. If the Euclidean distance between two Energy values 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. The FAR and FFR rates with different threshold values were obtained based on 100 × 400 = 40000 matches in each database. The FAR and FRR with different threshold values for DB1 and DB2 is shown in Table (I). The ROC for DB1 and DB2 databases is shown in Fig. 6. Which plots percentage of genuine individuals being accepted (GAR) against falsely accepted individuals (FAR) and each point on the curve corresponds to a decision criterion.

Threshold value	DB1		DB2	
	FAR (%)	FRR (%)	FAR (%)	FRR (%)
0.2	2.10	12.7	1.98	12.77
0.3	4.99	8.95	5.01	8.75
0.4	6.54	4.92	6.40	5.15

Table I: False Accept and False Reject Rates at Different Threshold Values for DB1 and DB2

5. Comparison

The performance of our proposed method is compared with the performance of: (a) Minutiae-based method [5], that doesn't use texture information for fingerprint representation and doesn't utilize rich discriminatory information component available in the ridges of a fingerprints and; (b) Filterbank-based method [10], that uses texture based representation of a fingerprint and captures both the local and global information in a fingerprint as a compact 'FingerCode'. The accuracy of the proposed method is quantified in terms of the False Acceptance Rate (FAR) and the False Rejection Rate (FRR). A FAR of 4.99% and 5.01% were obtained for a FRR of 8.95% and 8.75% for DB1 and DB2 respectively, depending on the threshold value chosen as shown in Table (I). The Equal Error Rate (FAR=FRR) for the suggested method was found to be 7% that implies accuracy of 93%. For example, at a 1% FAR, the suggested method gives a Genuine Accept Rate of 70% while as Minutiae-based and Filterbank-based methods give a Genuine Accept Rate of 72% and 87% respectively.

6. Discussion

In this paper, we have attempted to obtain concealed information from the fingerprints that is beyond visual perception. We have done our experimentation with the texture features of Energy, Entropy, Local Homogeneity and Inertia obtained using SGLDM. Earlier these features were used in extraction of invisible information from MR images by Lerski et al in [14] and Mir et al in [15]. In this paper Energy texture feature of a fingerprint has demonstrated its use for obtaining information that can be used for fingerprint discrimination and accordingly for personal verification. Comparison of the proposed method has demonstrated its superiority in terms of simplicity, though not as accurate as other methods. The method is simpler for the following reasons. This method obviates the need to use a minutiae or a ridge of a fingerprint as a feature. It eliminates the problem of missing or spurious minutiae's and problem of efficiently matching two fingerprint images containing different numbers of unregistered minutiae points. Besides, no need is to locate the core as in the 'FingerCode' method. Secondly, no alignment of fingerprints is needed as in case of the correlation based method. In the suggested method, the feature extraction process is simple and needs less preprocessing. Further, much more grey level information of a fingerprint is used by the suggested method.

7. Conclusion

We have proposed use of statistical texture analysis of a fingerprint based on the spatial grey level dependence method (SGLDM) for discrimination and personal verification. The performance of the method was evaluated on BD1 and DB2 fingerprint databases of FVC 2002 to demonstrate usefulness of the feature for discrimination and personal verification. The preliminary results have been quite encouraging and demonstrate the usefulness of this method to discriminate between different persons and therefore, can be reasonably used for personal verification.

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