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Investigation of NGTDM and SGLDM in Statistical Texture Analysis

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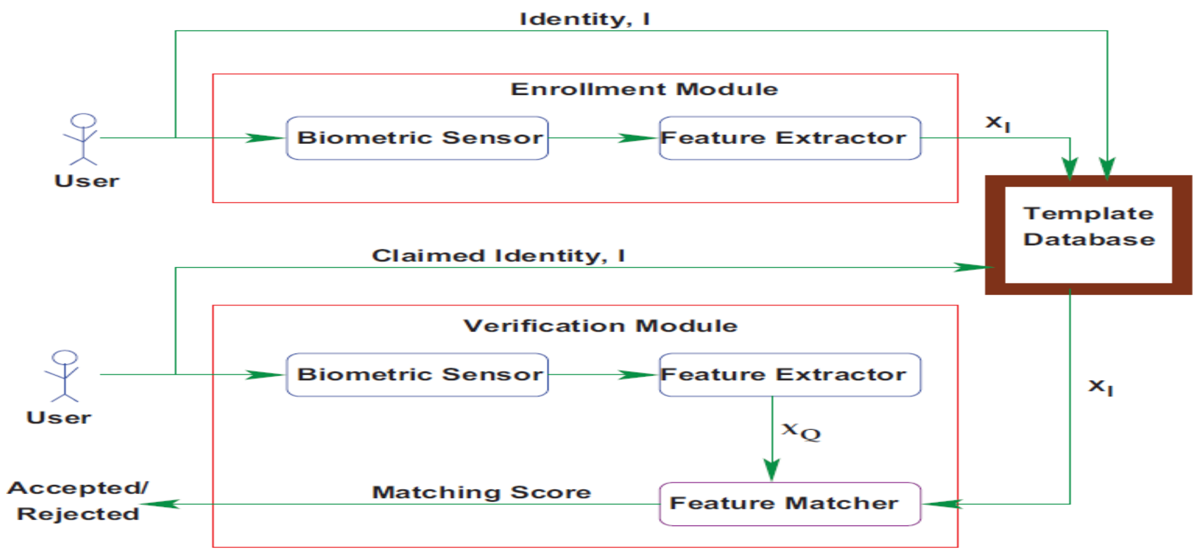
ABSTRACT:
Existing security measures rely on knowledge-based approaches like passwords or token based approaches such as swipe cards and passports to control access to physical and virtual spaces. Though ubiquitous, such methods are not very secure. Tokens such as badges and access cards may be shared or stolen. Furthermore, they cannot differentiate between authorized user and a person having access to the tokens or passwords .Biometrics such as fingerprint, face and voice print offers means of reliable personal authentication that can address these problems and is gaining citizen and government acceptance. Fingerprints were one of the first forms of biometric authentication to be used for law enforcement and civilian applications. Contrary to popular belief and despite decades of research in fingerprints, reliable fingerprint recognition is still an open problem. Reliable extraction of features from poor quality prints is the most challenging problem faced in the area of fingerprint recognition. In this thesis, we propose use of statistical texture analysis using Spatial Grey Level Dependence Matrix (SGLDM) for discrimination and personal verification, we also introduce a new approach for Statistical texture analysis of a fingerprint using Neighborhood Grey Tone Difference Matrix (NGTDM) based on textural features corresponding to visual properties of texture. Textural features corresponding to visual properties of texture are highly desirable for two main reasons. They will not be optimum in terms of feature selection but also be applicable to all kinds of textures. Results obtained from these two techniques are being compared to get the better feature selection technique for discrimination and personal verification.

INTRODUCTION:

Information security is concerned with the assurance of confidentiality, integrity and availability of information in all forms. There are many tools and techniques that can support the management of information security. The problem with the traditional approaches of identification using possession as a means of identity is that the possessions could be lost, stolen, forgotten, or misplaced. Further, once in control of the identifying possession, by definition, any other "unauthorized" person could abuse the privileges of the authorized user. The problem with using knowledge as an identity authentication mechanism is that it is difficult to remember the passwords/PINs; easily recallable passwords/PINs (e.g., pet's name, spouse's birthday) could be easily guessed by the adversaries. It has been estimated that about 25% of the people using ATM cards write their ATM PINs on the ATM card [1], thereby defeating possession/knowledge combination as a means of identification. As a result, these techniques cannot distinguish between an authorized person and an impostor who acquires the knowledge/possession, enabling the access privileges of the authorized person. Yet another approach to positive identification has been to reduce the problem of identification to the problem of identifying physical characteristics of the person. The characteristics could be either a person's physiological traits, e.g., fingerprints, hand geometry, etc. or her behavioral characteristics, e.g., voice and signature. This method of identification of a person based on his/her physiological/behavioral characteristics is called biometrics [2].

BIOMETRICS INTRODUCTION:
Biometrics (Ancient Greek: bios =”life”, metron =”measure”) refers to two different fields of study and application. The first, which is the older and is used in biological studies, including forestry, is the collection, synthesis, analysis and management of quantitative data on biological communities such as forests. Biometrics in reference to biological sciences has been studied and applied for several generations and is somewhat simply viewed as “biological statistics”. Authentication is the act of establishing or conforming something (or someone) as authentic, that is, that claims made by or about the thing are true[3]

BIOMETRICS VERIFICATION SYSTEMS:
Associating an identity with an individual is called personal identification. The problem of resolving the identity of a person can be categorized into two fundamentally distinct types of problems with different inherent complexities: Verification and Recognition (more popularly known as identification).
Verification (authentication) refers to the problem of confirming or denying a person's claimed identity (Am I who I claim I am?). Identification (Who am I?) refers to the problem of establishing a subject's identity - either from a set of already known identities (closed identification problem) or otherwise (open identification problem). Recognition is a generic term, and does not necessarily imply either verification or identification [4].



PERFORMANCE PARAMETERS:
The following are used as performance metrics for biometric systems [2]:

FALSE ACCEPT RATE OR FALSE MATCH RATE (FAR OR FMR):
The probability that the system incorrectly matches the input pattern to a non-matching template in the database. It measures the percent of invalid inputs which are incorrectly accepted.

FALSE REJECT RATE OR FALSE NON-MATCH RATE (FRR OR FNMR) :
the probability that the system fails to detect a match between the input pattern and a matching template in the database. It measures the percent of valid inputs which incorrectly rejected.

RECEIVER OPERATING CHARACTERISTICS OR RELATIVE OPERATING CHARACTERISTIC (ROC):
The ROC plot is a visual characterization of the trade-off between the FAR and the FRR. In general, the matching algorithm performs a decision based on a threshold which determines how close to a template the

input needs to be for it to be considered a match. If the threshold is reduced, there will be more false non-matches but less false accepts. Correspondingly, a higher threshold will increase the FAR and reduce the FRR. A common variation in the Detection error trade-off (DET), which is obtained using normal deviate scales on both axes. This more linear graph illuminates the differences for higher performances (rarer errors).

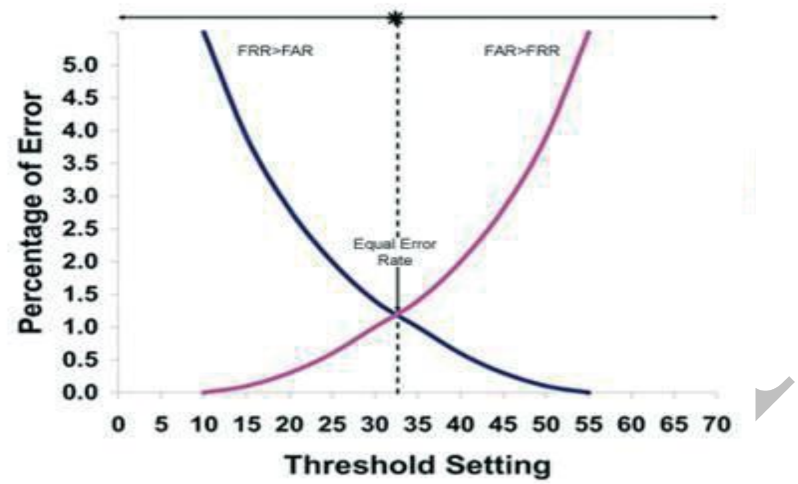


Figure Performance parameter comparison

EQUAL ERROR RATE OR CROSSOVER RATE (EER OR CER):
the rate at which both accept and reject errors are equal. The value of the EER can be easily obtained from the ROC curve. The EER is a quick way to compare the accuracy of devices with different ROC curves. In general, the device with the lowest EER is most accurate.

FAILURE TO ENROLL RATE (FTE OR FER):
the rate at which attempts to create a template from an input is unsuccessful. This is most commonly caused by low quality inputs.

FAILURE TO CAPTURE RATE (FTC) :
Within automatic systems, the probability that the system fails to detect a biometric input when presented correctly.

FINGERPRINT DATABASE:
The fingerprint images were taken from DB1 database of FVC 2002.

OBTAINING REGION OF INTEREST:
The images obtained from the database are converted to size of 240×245 to remove the redundant information as the blank has its own texture. Figure 1(a) shows the actual fingerprint chosen randomly from the said database and Figure 1(b) shows the cropped image.

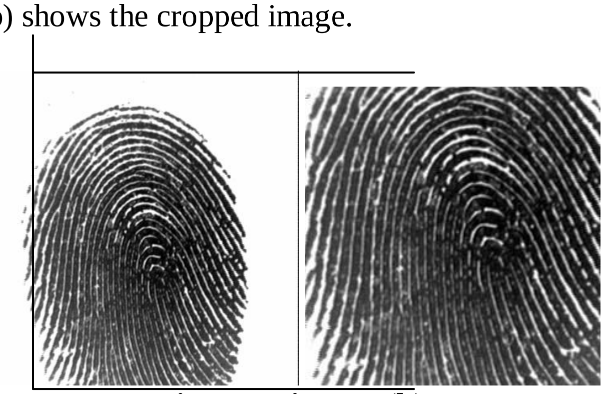


Figure 1Figure 1(b)
Figure (a) Actual fingerprint (b) Cropped image

FEATURE EXTRACTION

TEXTURE FEATURE EXTRACTION USING NGTDM:

Five different features were derived from the NGTDM, to quantitatively describe such perceptual texture properties as-

1. Coarseness

$$f_{\cos} = \left[\epsilon + \sum_{i=0}^{G_h} p_i s(i) \right]^{-1} \quad (1)$$

2. Contrast

$$f_{\text{con}} = \left[\frac{1}{N_g(N_g - 1)} \sum_{i=0}^{G_h} \sum_{j=0}^{G_h} p_i p_j (i-j)^2 \right] \left[\frac{1}{n^2} \sum_{i=0}^{G_h} s(i) \right] \quad (2)$$

3. Busyness

$$f_{\text{bus}} = \left[\sum_{i=0}^{G_h} p_i s(i) \right] \Big/ \left[\sum_{i=0}^{G_h} \sum_{j=0}^{G_h} ip_i - jp_j \right], \qquad p_i \neq 0,\ p_j \neq 0. \quad (3)$$

4. Complexity

$$f_{\text{com}} = \sum_{i=0}^{G_h} \sum_{j=0}^{G_h} \{ (|i-j|) / (n^2(p_i + p_j)) \} \{ p_i s(i) + p_j s(j) \}$$

$$p_i \neq 0,\ p_j \neq 0. \quad (4)$$

5. Texture Strength

(5)

METHODOLOGY:

SCATTER PLOT FOR SGLDM FEATURES:

Four features of SGLDM and five features of NGTDM of 20 subjects each having 8 samples are being calculated.

A scatter plot is being generated for each properties to check for their distinct values so that we can discriminate each subject easily. In this scatter plot the mean of 5 samples of each subject is plotted against its property values. Out of four features from SGLDM we get one feature Contrast having most distinct values from figure 1. The other SGLDM features such as correlation the values of each fingerprint are nearly same so it is very difficult to discriminate them as we can see from figure (b). The features energy and homogeneity have distinct values but the range of values for each fingerprint is very small to discriminate.

SGLDM CONTRAST:

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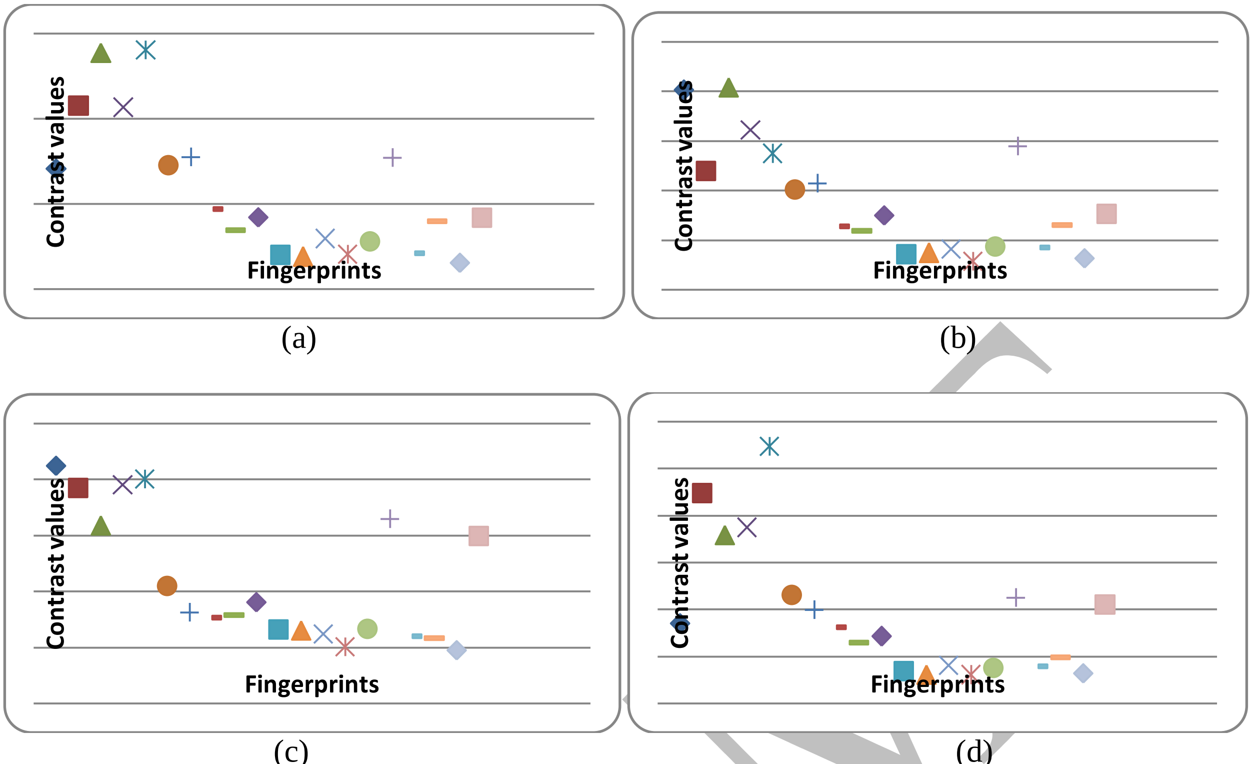

Figure. (a),(b),(c),(d) SGLDM Contrast at 0,45,90,135 degrees respectively

SGLDM Correlation

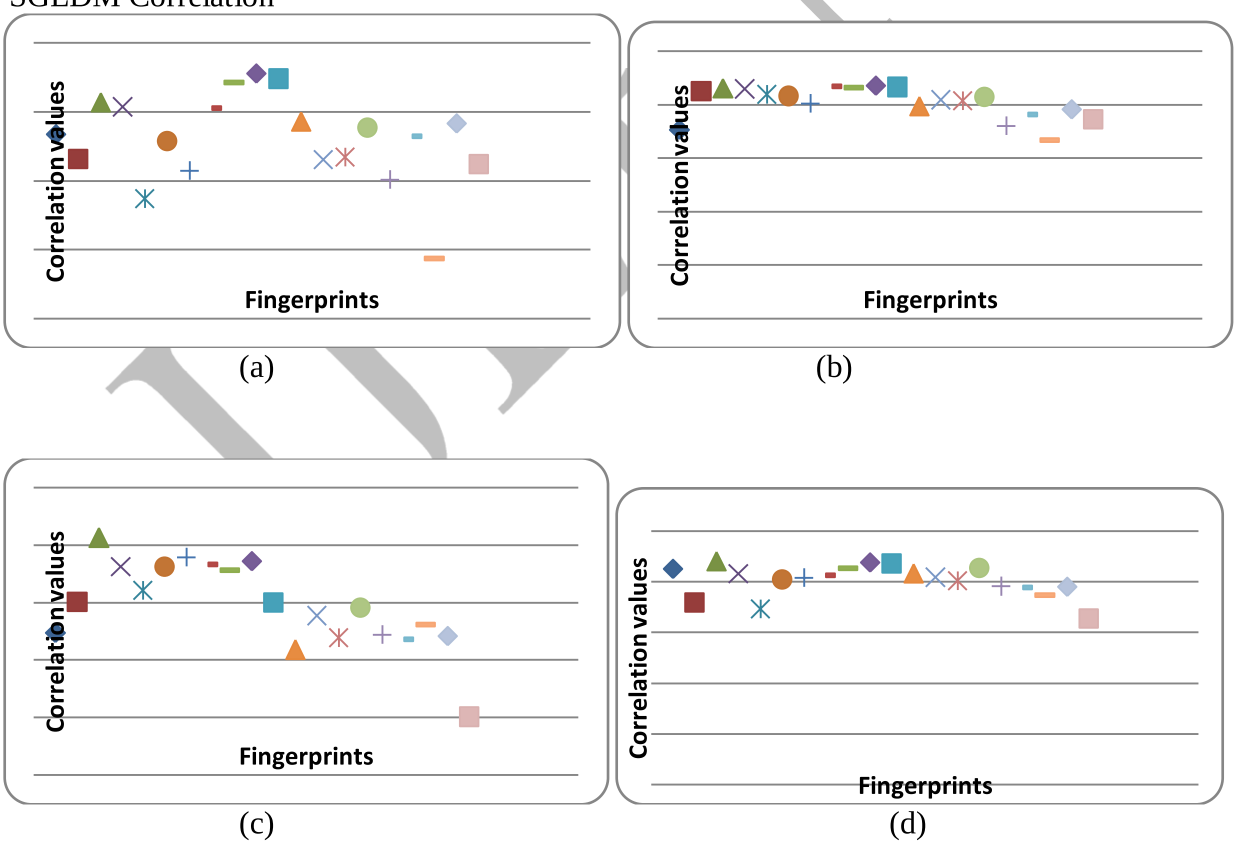

Figure.(a),(b),(c),(d) SGLDM Correlationt at 0,45,90,135 degrees respectively

GENUINE AND IMPOSTER DISTRIBUTION FOR SGLDM AND NGTDM FEATURES:

In Genuine and Imposter distribution we can see the two population areas – one being genuine and one being imposter. In the overlap region between these two populations it is not easy to classify if a score is genuine or imposter.

There will always be varying degrees of overlap region in any biometric system. The smaller the overlap region, the more accurate the biometric system is thought to be.

In Genuine and Imposter distribution plot given below the minimum overlap region for SGLDM feature is at 0 degree as shown in figure 5.6 and for NGTDM it is for Coarseness feature as shown in figure 5.10.

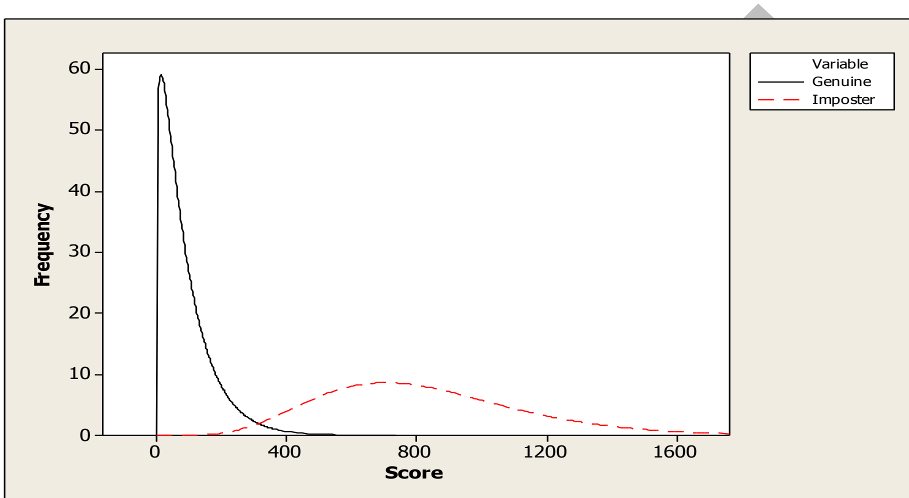

Figure 5.6. Genuine and Imposter Distribution for SGLDM 0 degree

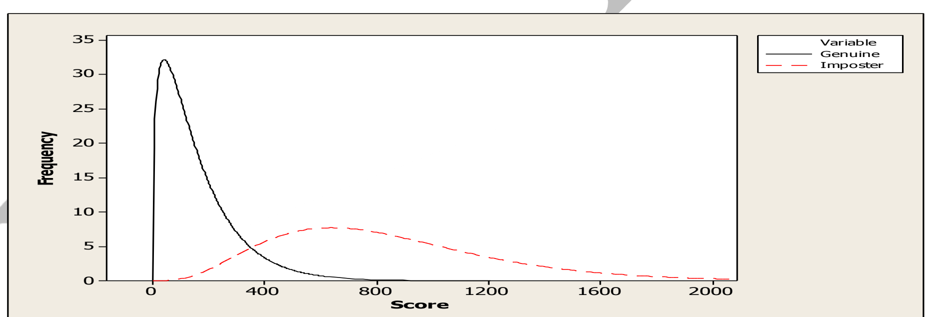

Figure Genuine and Imposter Distribution for SGLDM 45 degree

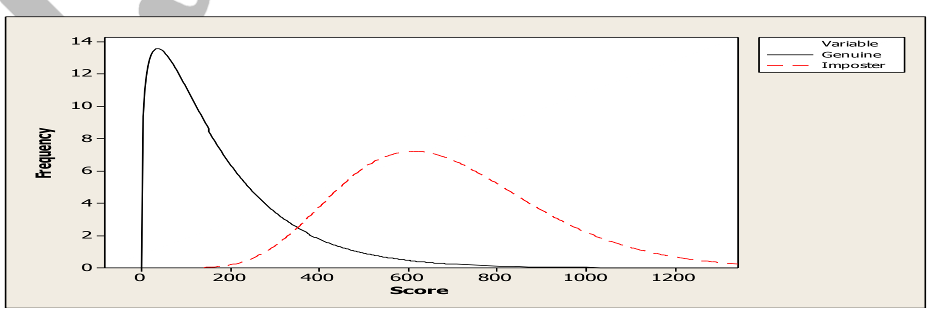

Figure Genuine and Imposter Distribution for SGLDM 90 degree

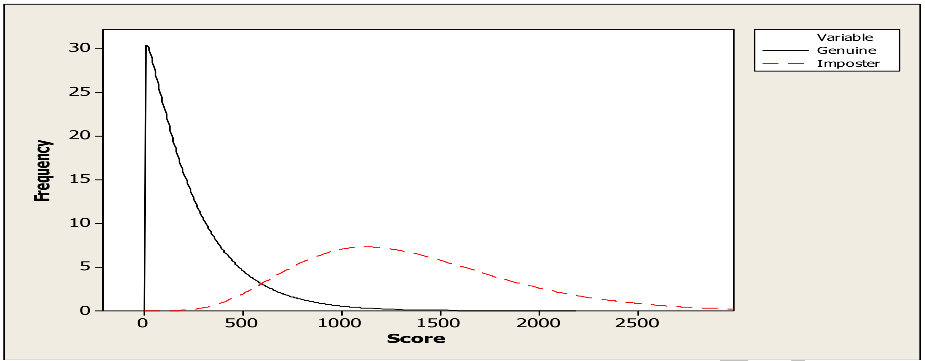

Figure Genuine and Imposter Distribution for SGLDM 135 degree

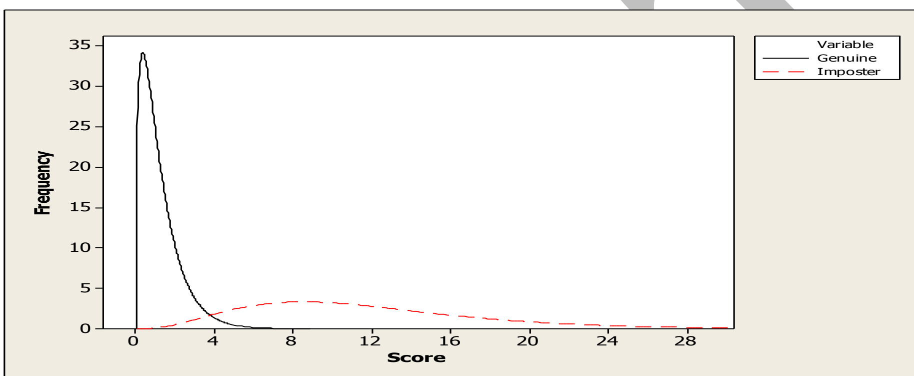

Figure Genuine and Imposter Distribution for NGTDM Coarseness

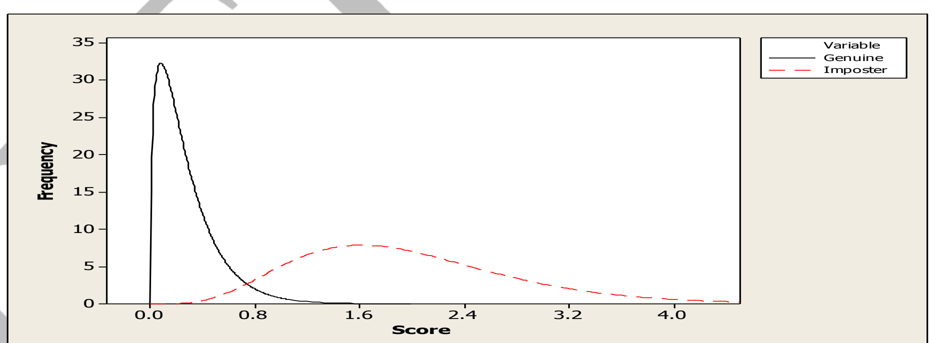

Figure Genuine and Imposter Distribution for NGTDM Contrast

CONCLUSION AND FUTURE WORK:

In this thesis our main objective was to check the potential of texture based techniques for verification of a person. NGTDM features have never been tested for fingerprint verification and also never been compared with the SGLDM features for fingerprint verification. The Database FVC 2002 has been used for comparison. The Equal Error Rate(FAR=FRR) obtained for SGLDM contrast feature at 0 degree is 14% that implies the accuracy of 86% whereas for NGTDM coarseness feature is 24% having accuracy of 74%. The FAR is 5% and 14% respectively which means that the NGTDM feature could not be used for high security purposes. NGTDM features are used corresponding to visual properties of texture and SGLDM features are used for the texture which are beyond visual perception. The performance statistics obtained from this test showed SGLDM feature is better than NGTDM features and can be used with Euclidean distances for an offline fingerprint verification. Thus the conclusion is that the features based on visual perception are less effective than the features based beyond the visual perception.

As future work we are going to investigate more relevant features by the fusion of features of both the statistical texture analysis technique that is NGTDM as well as SGLDM. Using a mixture of features may lead to high performance fingerprint verification system. These features can also be used for other biometric techniques for their generalist nature and prove to be beneficial.

The performance of these techniques can also be enhanced by using some other classifiers such as Mahalanobis distance. Unlike the Euclidean distance that uses the mean vector, Mahalanobis distance uses both the mean vector and the full covariance matrix which can be an efficient measure of variability among fingerprints. The experiment can also be extended to combine two or more of these distance measures and compare their efficiency. The other classifiers we can use for better classification are SVM,HMM,NN and compare the technique.

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