Fingerprint Recognition System Using Multiple Representations

Aranuwa, F. O.
Department of Computer Science
Adekunle Ajasin University
Akungba – Akoko,
Ondo State, Nigeria,
(felix.aranuwa@aaua.edu.ng).

ABSTRACT

Recent advances in automated fingerprint recognition systems coupled with the growing need for reliable and efficient identification system have resulted in an increased deployment of fingerprint biometric technology in many broad applications. The system has been adjudged one of the most publicized biometrics across the globe as it offers reliable means of personal identification because of its uniqueness and consistency over time. Fingerprint recognition system has been successfully used in law enforcement and forensics to identify suspects and victims for over a century. It is very relevant in border and access control, employment background checks, students' examinations and class attendance, user authentication on laptops and mobile devices et.c. Yet, there are number of challenges that recedes the effectiveness of the system. For instance, errors in matching process that particularly occur in many applications with single mode representation due to distortions and noisy data. Consequently this has led to a significant reduction in the accuracy of the system. Therefore, this research work is focused at considering fingerprint recognition system using multiple representations. Specifically, minutiae and texture based fingerprint representations are considered. Samples data collected for the research work were trained and tested using the classifiers system designed for the work. The approach was found to be more robust than the single mode representation in terms of accuracy and speed.

Keywords: Fingerprint recognition, Matching process, Unimodal biometric, Multiple representations, Fusion techniques

ISTEAMS Cross-Border Conference Proceedings Paper Citation Format

Aranuwa, F.O. (2017): Fingerprint Recognition System Using Multiple Representations.
Proceedings of the 9th iSTEAMS Multidisciplinary Conference, University of Ghana, Legon, Accra Ghana. Pp 115-126.

1. BACKGROUND TO THE STUDY

By definition, fingerprint recognition is referred to the automated method of identifying or confirming the identity of an individual based on the comparison of their fingerprints (Samayita and Bhattacharya, 2014). It is one of the most well known biometrics across the globe for personal recognition and identification on computerized systems. Fingerprint identification is popular because of its uniqueness and inherent ease in acquisition (Kalyani and Mali, 2014). It has been successfully applied in law enforcement and forensics to identify suspects and victims for over a century. However, in spite of its applications in many large-scale and diverse person identification systems, yet there are some challenges that draws back the efficiency of the system more importantly in single mode representation system where matching process errors do occur due to distortions and noisy data (Samayita and Bhattacharya, 2014; Yoon, 2014). The overture of multiple biometric technologies is focused at overcoming the limitations of unimodal biometric system. The later technology combines evidences from multiple biometric sources such as multimodal, multiple instances or representations). Such systems are more robust to variations in sample quality offering considerable improvements in reliability with reasonably overall performance in many applications than unimodal systems (Aranuwa, 2014). For the purpose of this research work, multiple representations based on minutiae and texture fingerprint features were considered.

1.1 Fingerprint Features and Pattern

A fingerprint is a pattern of feature of a finger and it is believed that every person possesses unique fingerprints. Figure 1.1 shows the features of a typical fingerprint.

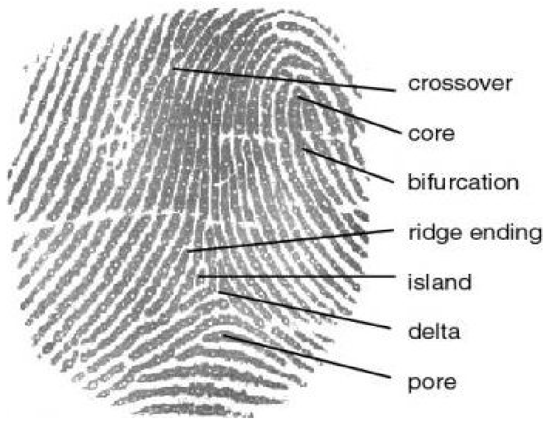
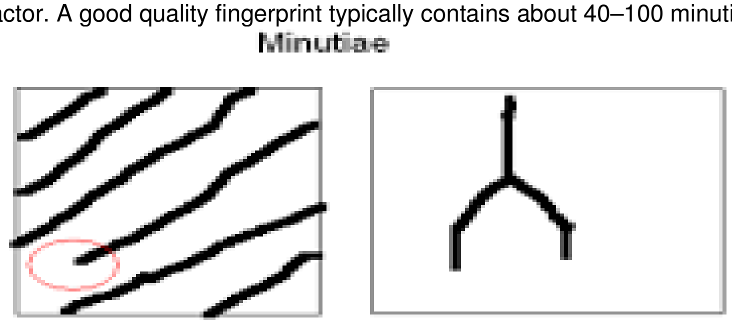


Figure 1.1: Typical fingerprint image taken through an optical sensor.
Source: (Fingerprint from FVC2002)

According to Xuejun and Bir (2006), fingerprint has pattern of ridges and valleys on the surface of a fingertip. The endpoints and crossing points of ridges are called minutiae; the minutiae ending and bifurcation are shown in Figure 1.2. By description, bifurcation is a ridge point where a ridge bifurcates into two ridges. It is a widely accepted assumption that the minutiae pattern of each finger is unique and does not change during one's life time. To determine if two fingerprints are from the same finger, the matching degree between two minutiae pattern is one of the most important factor. A good quality fingerprint typically contains about 40–100 minutiae (Zaeri, 2011).



(a) Ridge ending (b) bifurcation

Figure 1.2: The image of fingerprint showing the ridge ending and bifurcation
Source: Xuejun and Tan, (2006)

According to Ritu and Matish, (2014), there are two types of minutiae: these are the termination and bifurcation. The termination is the immediate ending of a ridge, while the bifurcation is the point on the ridges where two branches bifurcated. Figure 1.3 and figure 1.4 show the different views of termination and bifurcation respectively.

.

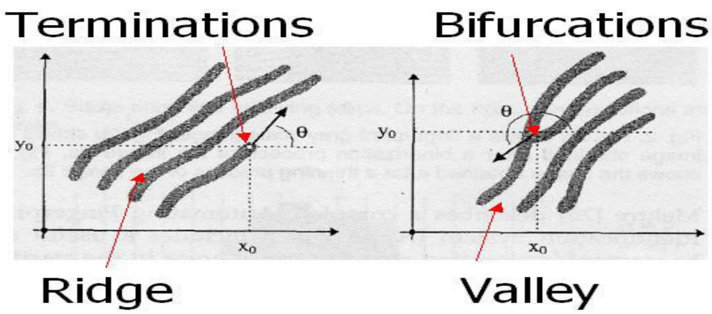


Figure 1.3 Minutiae (termination and bifurcation)
Source: Ritu and Matich, (2014)

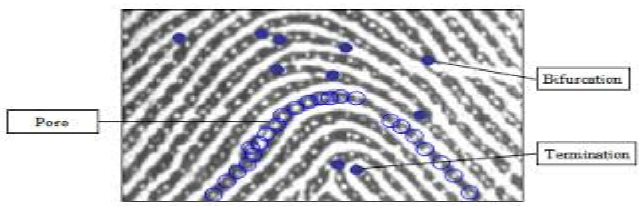


Figure 1.4: Minutiae (termination and bifurcation)
Source: Manvjeet et al, (2008)

A fingerprint image type is of three basic patterns as depicted in Figure 1.5. The first one is the Loop with one or more ridges entering and exiting from same side in a curvy form of fingerprint. The loop is of two types and these are the left loop and right loop. The second pattern is called the Whorl. The whorl could be plain, central pocket, double loop, or accidental. The Plain whorls have at least one ridge that makes a complete circuit and an imaginary line from one delta to the other ones that must touch a whorl ridge. The central pocket whorl is the type that has at least one ridge that makes a complete circuit and an imaginary line from one delta to the other that does not touch a whorl ridge. The double loop is two loops combined to make one whorl. Any other types not in these three categories are called accidentals. The third pattern is called the Arch, in this pattern; the ridges enter from one side and leaves out from the other side. They are of two type i.e the tented arch and plain arch. (Kaur and Narwal, 2016).

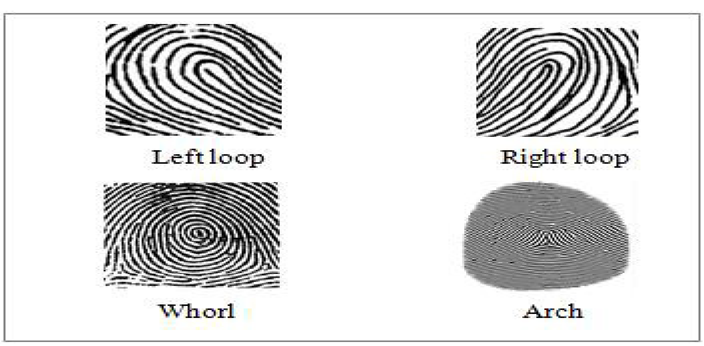


Figure 1.5: Fingerprint types showing arch, loop and whorl patterns
Source: (Kaur and Narwal, 2016).

Generally, in biometric system, the scheme for object recognition usually involves three important stages: The first one is the extraction of salient feature points from both the test and model object. The second stage is the template generation while the final stage is the matching between the test and model images based on the extracted features. (Ross and Jain, 2004). According to Nadarajah and Celattin (2011), all fingerprint recognition systems follows a two stage process (i.e the enrolment and identification process). Each of the process consists of several sub-processes. Figure 1.6 illustrates these processes.

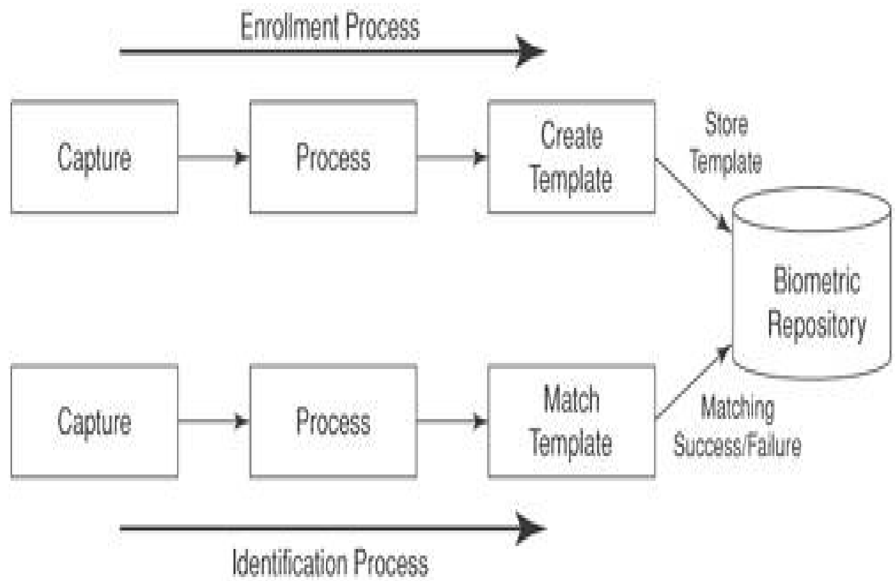


Figure 1.6: Fingerprint recognition enrolment and identification processes (Nadarajah and Celattin, 2011)

1.2 Fingerprint Feature Extraction and Algorithms

According to Ali, Xiaojun and Saleem (2011), fingerprint recognition feature extraction and matching are mainly done by algorithms and these algorithms are largely based on minutiae details, image correlation and texture analysis. The Minutiae based fingerprint recognition system is one of the generally accepted fingerprint biometric recognition system. It involves the extraction of the minutiae sets from the fingerprints and the query images, establishing the alignment between the two minutiae sets and the calculation of match score based on the number of correspondences between the two minutiae sets. In the correlation-based recognition, the query and the template images are superimposed and the image correlation is carried out between the corresponding pixels for different alignments. Meanwhile, this method has been found to be computationally expensive and in addition to its sensitivity to non-linear distortion, it makes two impressions of the same fingerprint different from one another.

An alternative to minutiae is the texture based fingerprint biometric system. They are spatial repetition of the basic fingerprint elements characterized by properties such as scale, orientation, frequency, symmetry, and isotropy. They are usually extracted using the spatial grey level dependence matrix (SGDLM) method. SGLDM is one of the most popular methods for extracting statistical texture features. In this method, the texture information of the image is to find the similarity and differences between the images captured. It is very useful for low quality images more importantly where the minutiae details cannot be extracted. The texture based fingerprint is of two types, the global and the local. However, the local texture analysis has proved to be more effective than global feature analysis (James et al, 2009). Texture fingerprint classification is based on features, such as Entropy, Energy, and Correlation. Entropy is a measure of uncertainty in a random variable. It is a quantity which is used to describe the production of an image i.e. the amount of information which must be coded for by a compression algorithm. According to *Kaur and Narwal, (2016),* energy in image processing has different meaning depending on the context of where it is used.

For instance, in signal processing, "energy" corresponds to the mean squared value of the signal (typically measured with respect to the global mean value). This concept is usually associated with the Perceval theorem, which allows the total frequency as distributed frequencies, while the correlation is an optical method that employs tracking and image registration techniques for accurate 2D and 3D measurements of changes in the images. This is used to describe a measure of information when formulating an operation under a probability framework. By extracting these features, 100% accuracy is achievable.

Fingerprint recognition can also be achieved by Principal Component Analysis (PCA) and Independent Component Analysis (ICA) (Wang, Jing, Zhu, Sun and Hong (2007). PCA is a classical statistical method; it transforms the source data into a new orthogonal coordinate system and maps the multi-dimensional data into a lower dimension space with minimal loss of information (Rajagopalan, Chellappa and Koterba, 2005). The optimal dimensionality reduction in matrix principal components analysis is obtained by truncation of the singular value decomposition. The ICA is a data analysis tool derived from the 'source separation' signal processing technique. The basic ideal of ICA is to represent a set of random variables using basic component, where the components (basic functions) are statistically independent as possible. The ICA for multivariate data computes second and higher-order pixel statistics by seeking a sequence of projections such that the projected data appear as far from Gaussian as possible. Others are Reference Point Algorithm (RPA) and Wavelet Feature Extraction (WFE). For the purpose of this paper, the minutiae and texture based algorithms, the adjudged most widely used and accepted fingerprint algorithms are considered.

Researchers at different levels have proposed and used minutiae and texture based representations in different applications independently. The research works of Venkatesh and Ambeth (2013), Manvjeet et al (2008), Jain, Kong, Pankanti and Bolle, (1997) which was later re-modified in 2010 were all based on Minutiae representation while that of Zahoor, Mir and Rubab, (2011) and, Zin and Sein, (2011) were based on texture representation. However, in this research work, effort is focused at considering the performance of the minutiae and texture representations in a single application. See figure 1.7(a) and (b) show the images of minutiae and texture based representations.

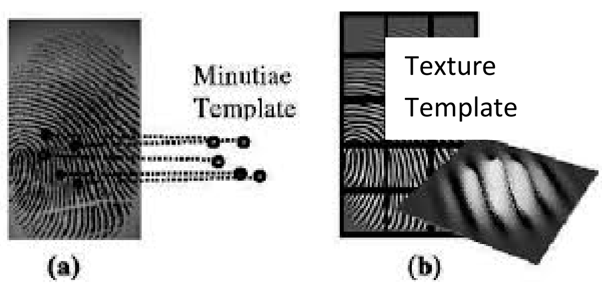


Figure 1.7 (a) Minutiae based fingerprint representation and (b): Texture based fingerprint representation

1.3 Statement of Problem

Fingerprint recognition has been adjudged one of the most well used biometrics solutions for identification and authentication systems as a result of its uniqueness and consistency over time. However, in spite of its application in many large-scale and diverse person identification systems, yet there are some challenges that draw back the efficiency of the system more importantly in single mode representation biometric system where matching process errors occurs due to distortions and noisy data. Consequently this has led to a significant reduction in the accuracy of the system. Researchers at different levels have proposed different approaches and algorithms in unimodal biometric system; however the issue of efficiency and precision of the system remains a big challenge. Since biometric systems are resource intensive in terms of processing speed and accuracy thus the need for an effective approach for optimal performance of fingerprint recognition system.

1.4. Objective

The aim of this research work is to develop a fingerprint recognition system using multiple representation of based on minutiae and texture representations for reliable and efficient fingerprint recognition systems.

2. METHODOLOGY

2.1 The Research Design

Figure 7 shows the architecture of the proposed system. The structural design for the research work is composed of six major modules, namely: the feature extraction, pre-processing and template generation, database, matching, fusion and the decision modules.

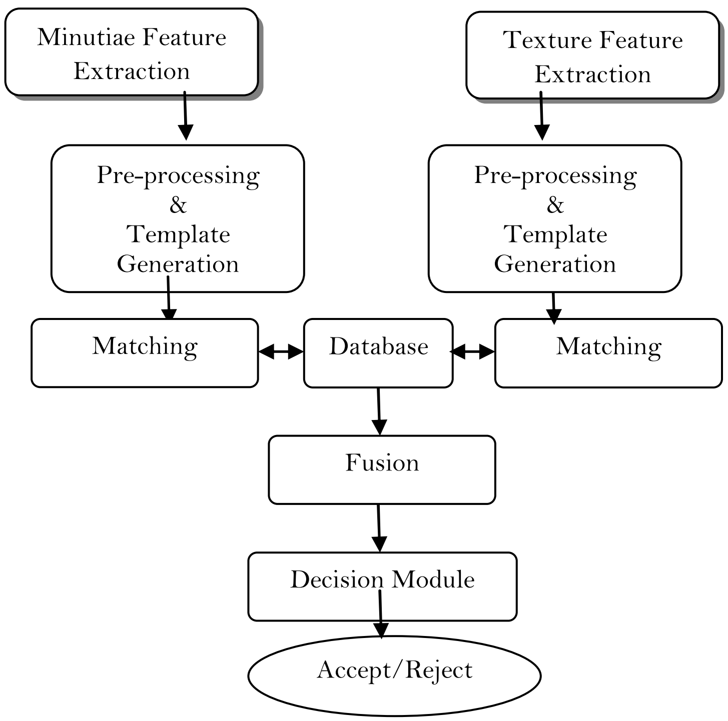


Figure 7: Research Design for the proposed system

The feature extraction module is responsible for the image acquisition and extraction of salient features to represent underlying fingerprint representation. The feature extraction process entails reading and codifying each of the minutiae and texture features. The captured image is then processed using image enhancement techniques to improve its quality and the resulting image is reported in a binary form. The image enhancement in this work was done using Fourier Fingerprint Transform (FFT). In the enhancement process, the images were divided into small processing blocks of 32 by 32 pixels. The Fourier Transformation on each block was performed using the following equation:

$$f(u,v) = \sum_{x=0}^{m-1}\sum_{y=0}^{n-1} f(x,y) \times \exp\left\{-j2\pi \times \left(\frac{ux}{M}+\frac{uv}{N}\right)\right\}$$ ....Equation 1

$$for\ U = 0,1,2,3 \ldots 31\ and\ V = 0,1,2,3 \ldots 31$$

In order to enhance each block by its dominant frequencies, each block after FFT was multiplied with its magnitude a set of times. The formula for the magnitude is given as:

$$abs\big(f(u,v)\big) = |f(u,v)| \text{ ... Equation 2}$$

And the enhanced block is based on:

$$g(x,y) = F^{-1}\{F(u,v) \times |F(u,v|^{k}\} \text{... Equation 3}$$

Where $F^{-1}\{F(u,v)$ is given by:

$$F(x,y) = \frac{1}{MN}\sum_{x=0}^{m=1}\sum_{y=0}^{n=1} F(u,v) \times \exp\left\{j2\pi \times \left(\frac{ux}{M} + \frac{vy}{N}\right)\right\} \text{... Equation 4}$$

$$for\ x = 0,1,2,3 \ldots 31\ and\ y = 0,1,2,3 \ldots .31$$

The k in the formulae is a constant which is determined experimentally according to *Gouda et al (2012*).

During the enrolment, the feature set is stored in the database commonly referred to as a template. The system database module acts as the repository of the fingerprint information. The matching module compares new extracted features against the stored template to generate match scores. The number of matching features between the input and the template feature sets is determined, and a match score is reported. The decision module uses the match scores to either validate a claimed identity of the user's identity or decides otherwise.

3. DATA PRESENTATION

The model developed for the research work was able to extract and convert successfully 50 images each of the fingerprints captured for both minutiae and texture features using standard enrolment devices with 500 dpi. The parameters, such as number of directions in the orientation field were determined by running the algorithm on sets of the test images. Figure 8 shows the data acquisition platform.

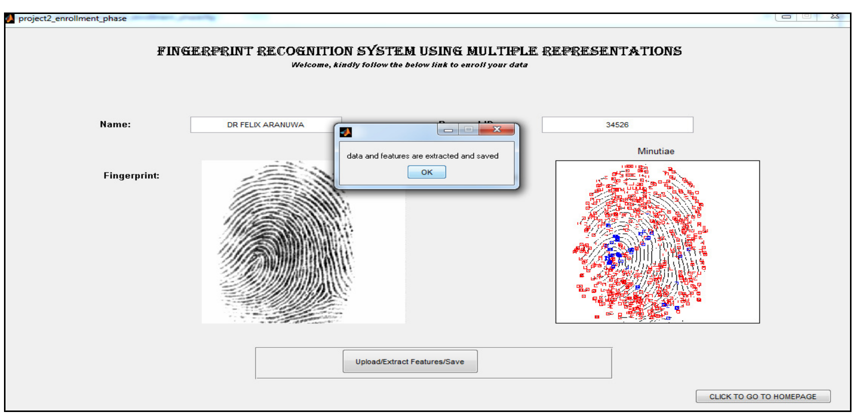


Figure 8: Data capture platform

In the feature extraction module, the x_location and y_location of the minutiae feature were determined and the Euclidean distance between the ridge ending and bifurcation were calculated as reported in Table 1.

Table1: Sample data

Fingerprint Image	x_location	y_location	Euc_Distance	Texture_value
Sample 1	944	49	9	25
Sample 2	1025	23	10	50
Sample 3	487	39	4	36
Sample 4	846	127	7	48
"	"	"	"	"
Sample 50	732	12	7	44

The minutia matching was done using the Rutovitz concept of crossing number algorithm, which is defined as follows:

$$C_n\ (P) = (\frac{1}{2})\sum_{i=1}^{N}|P_i - P_{i+1}|\ .$$ ……………………………………….……….….. Equation 5

Where
Pi is the binary pixel value in the neighborhood of P with Pi = (0 or 1) and P1= P9.

The crossing number $C_n(P)$ at a point P is defined as half of cumulative successive differences between pairs of adjacent pixels belonging to the N- neighborhood of P.

Mathematically,

$$R_N = \sum([C_n(p) \geq 2]) \ldots (\ summation\ of\ the\ ridge\ ending)$$

$$B_N = \sum([C_n(p) \geq 1]) \ldots .(summation\ of\ burfication\ Ending)$$

$$T_N = \sqrt{sum((R_N - B_N))^2}$$ ………………………………..Equation 6

R_N and B_N are the $ridge\ ending$ and $burfication\ Ending$ respectively, while; T_N is the value that will be used for matching with other minutiae value gotten for authentication.

The texture features extraction was done using the SGDLM method. The model is mathematically stated as follows:

$$Contrast = f_1 = \sum_{i,j} |i-j|^2\, p(i,j) \ldots\ldots\ldots\ldots\ldots \text{ Equation 7}$$

$$Correlation = f_2 = \sum_{i,j}^{N} \frac{(i-\mu_i)(j-\mu_i)p(i,j)}{\sigma_i \sigma_j} \ldots \text{ Equation 8}$$

$$Energy = f_3 = \sum_{i,j} p(i,j)^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{ Equation 9}$$

$$Homogeniety = f_4 = \sum_{i,j}^{N} \frac{p(i,j)}{1+|i,j|} \ldots\ldots\ldots\ldots\ldots \text{ Equation 10}$$

$$f_5 = [f_1 \quad f_2 f_3 \quad f_4] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{ Equation 11}$$

$$f_6 = Matrix_{sum[f_5]} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{ Equation 12}$$

$$f_7 = \frac{f_6}{1000} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{ Equation 13}$$

The texture values from the texture based fingerprints were taken and the mean threshold value of all feature vectors was calculated. During matching process, the thresholds values from both enrolled and verifiable fingerprint were compared to find the similarity and differences between the images.

3.1 Fusion of the Minutiae and Texture features

Generally, fusion in biometric systems can take place at four major levels, namely the sensor level, feature level, score level and decision level. The four levels could further be categorized into: pre-classification (fusion before matching) and post classification (fusion after matching) (Sanderson and Paliwal, 2002). Meanwhile, the common practice is to combine evidences after the matching score level, which is the approach adopted in this work. The approach is also known as fusion at the measurement level or confidence level. At this level the biometric matchers output a set of possible matches along with the quality of each matching score and this makes it relatively easy to access and combine. Different fusion techniques such as rule based, statistical methods and machine learning algorithms has been discussed in literatures and proposed for biometric information fusion at different levels. In this work, a linear summation rule technique was used. The threshold value of the minutiae point and the energy texture feature were fused .The result of the concatenation was then stored in the database. The fusion equation is stated as follows:

$$\boldsymbol{Fus} = (T_N + f_7)\frac{1}{2} \ldots Equation\ 14$$

T_N is the minutiae matching value and,

Let f_7 is the matching texture value.

4. DISCUSSION OF FINDINGS

A total number of 50 comparisons for the three sets of experiment conducted were performed and values for accuracy (similarity scores) and time taken were analyzed for each approach. Performance analysis of the algorithms implemented in the research was done using the descriptive statistics in SPSS. The minimum and maximum values of occurrence, average mean, the standard deviation, range and variance of the two representations' algorithm considered were computed as shown in table 2 and table 3. Table 4 shows the performance of the fusion technique.

Table 2 – Performance of the Texture Based Algorithm

Descriptive Statistics	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
ACCURACY	50	423	105	528	328.40	106.4	11,336.898
SPEED	50	753	95	848	323.58	196.918	38,776.575
Valid N (list wise)	50						

Table 3 – Performance of the Minutia Based Algorithm

Descriptive Statistics	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
Accuracy	50	35.21	60.78	95.99	76.3601	92.47	85.520
Speed	50	98.00	1,000.00	1,098.00	1,044.4600	29.40721	864.784
Valid N (list wise)	50						

Table 4 – Performance of the Fusion Technique

Descriptive Statistics	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
ACCURACY	50	325	85	410	67.40	71.42	65.80
SPEED	50	650	75	725	258.5	18.4	638.7
Valid N (list wise)	50						

The results of the research experiments revealed that the minutiae fingerprint matching algorithms require high computational resources in terms of speed, time and memory. For instance, it took approximately thirty (30) minutes to perform de-duplication of fifty (50) candidates fingerprint images each on a personal laptop. It was also observed that the texture based algorithms performs better than that of minutiae in terms of speed with an average of 323.58 milliseconds and standard deviation of 106.47 compared to the minutia based algorithm with an average of 1,044.46 milliseconds and standard deviation of 92.47 respectively. However, the integration algorithm for the duo performed better in terms of speed and accuracy with an average of 258.5 milliseconds and standard deviation of 71. 42 respectively.

The performance metrics considered for the experiment is the measure of the errors in terms of false acceptance rate (FAR), false rejection rate (FRR), failure to enroll rate (FER), during enrollment and verification time. False Acceptance Rate (FAR) is defined as the ratio of impostors that were falsely accepted over the total number of impostors tested described as a percentage. (i.e FAR = Number of accepted imposter claims / Total number of imposter accesses x 100%). Using the threshold value of 5.93 for minutiae and threshold value 31.9 for texture for 15 trials or instances of trial: the FRR is 20%, the FAR is 25%. Averagely, the percentage rate that the system will authenticate an authorized user in 15 trials is 80%.

5. CONCLUDING REMARKS

This research work considered fingerprint recognition system using multiple representations. Specifically, minutiae and texture based fingerprint representations were considered. Samples data of fingerprints images from Fifty (50) candidates were collected trained and tested using the classifiers system designed for the work. The classifiers performance analysis for the duo was conducted and experimental results show that the fusion of the duo was found to provide better results in term of accuracy and speed than the independent feature representation.

6. CONTRIBUTION TO KNOWLEDGE

The research work has presented an efficient approach for fingerprint authentication and identification system. With this approach, problem of time and computational complexity can be circumvented. The method is believed to improve the reliability, accuracy and reduce error rate in fingerprint recognition system.

REFERENCES

1. Samayita B and Kalyani M (2014): Comparative study of Different Filters on images in Frequency Domain. International Journal of Advance Research in Computer science and Software Engineering, Volume 4 Issue8.
2. Kalyani M. and Samayita B (2014). Fingerprint Matching Using Correlation (In Frequency Domain). Department of Computer Science & Engineering, University of Kalyani, Kalyani, West Bengal, India
3. Yoon, S (2014): Fingerprint Recognition: Models and Applications A Dissertation Submitted to Michigan State University, in partial fulfillment of the requirements for the degree of Computer Science – Doctor of Philosophy.
4. Aranuwa F. O (2014): Multiple biometric systems: design approach and application Scenario Elixir International Journal, Volume 73 pg 26015-26019.
5. Xuejun, T and Bir, B. (2006), “Fingerprint matching by genetic, algorithms, Pattern Recognition Society. *Published by Elsevier Ltd*, 39 pp: 465-477, 2006.
6. Zaeri , N (2011). Minutiae-based Fingerprint Extraction and Recognition, Biometrics, ISBN: 978-953-307-618- 8, InTech, Available from: http://www.intechopen.com/books/biometrics/minutiae-based-fingerprint-extraction-and-recognition.
7. Ritu and Matish Garg,(2014). A review on Fingerprint-based Identification system
8. Manvjeet Kaur, Mukhwinder Singh, Akshay Girdhar and ParvinderS. Sandhu, (2008). Fingerprint Verification system Using Minutiae Extraction Techniques at World Academy of Science, Engineering and Technology Vol 2, 14.
9. Kaur, D and Narwal S (2016): Comparison between Minutiae Based and Pattern Based Algorithm of Fingerprint Image. I.J. Information Engineering and Electronic Business, 2016, 2, 23-29 Published Online March 2016 in MECS (http://www.mecs-press.org/) DOI: 10.5815/ijieeb.2016.02.03.
10. Ross, A. and Jain, A.K. (2007), Human Recognition using Biometrics: An Overview: Annals of Telecommunications, Vol.62, No. 1 pp.11-35.
11. Nadarajah. M and Celattin. T (2011), Fingerprint Biometric for Identity management International Journal of Industrial Engineering and Management (IJIEM), Vol. 2 No 2, 2011,
12. Ali, A. Xiaojun, J and Saleem, N (2011): GLCM-Based Fingerprint Recognition Algorithm” Broadband Network and Multimedia Technology (ICBNMT), 2011 4th IEEE International Conference on Digital 2011, PP: 207 – 211.
13. James W., Anil J, Davide M and Dario M (2009).Handbook of Fingerprint Recognition
14. Wang Yuan ; Yao Lixiu ; Zhou Fuqiang ,” A Real Time Fingerprint Recognition Based On Novel Fingerprint Matching Strategy System ” Electronic Measurement and Instruments, 2007. ICEMI '07. 8th International Conference , 2007 , PP: 1-81 - 1-85
15. Rajagopalan, A.N., Chellappa, R., Koterba, N.T (2005): Background learning for robust face recognition with PCA in the presence of clutter;” Image Processing, IEEE Transactions on Volume 14, Issue 6, June 2005 PP: 832 – 843.

16. Venkatesh, J and Ambeth K.V.D (2013): Advanced Filter and Minutia Matching For Fingerprint Recognition. International Journal of Science and Research (IJSR), India Online ISSN: 2319-7064.
17. Jain, A. K., Hong, L., Pankanti, S., & Bolle, R. (1997). An identity-authentication system using fingerprints. Proceedings of the IEEE, 85(9), 1365-1388.
18. Zahoor, Mir and Rubab, (2011): Human Verification using Multiple Fingerprint Texture Matchers. Computer Engineering and Intelligent Systems www.iiste.org ISSN 2222-1719 (Paper) ISSN 2222-2863 (Online) Vol 2, No.8.
19. Zin M. W, Sein, M.M (2011): " Texture Feature based Fingerprint Recognition for Low Quality Images" Micro-NanoMechatronics and Human Science (MHS), 2011 International Symposium 2011, PP 333 – 338.