A Multi-Level Fingerprint Recognition System Based On Minutiae And Non-Minutiae Descriptors

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ABSTRACT

Fingerprint recognition has been described as one of the most well known and used biometrics solutions for identification and authentication systems in many biometric applications as a result of its uniqueness and consistency over time. However, the search for the best possible descriptor and optimal algorithm for fingerprint enrollment and identification remains a major research issue. Various fingerprint descriptors have been proposed in the literature. The two main categories can be classified into minutiae and non-minutiae descriptors. Minutiae based descriptors are the most popular algorithm and have been used in many fingerprint applications. Meanwhile, an important alternative is the non-minutiae descriptor which classically is texture-based. Researchers at different levels have used the descriptors and different verification methodologies independently and by fusion. Despite these advances, the challenges of structural feature extraction, errors in matching and large computational requirements still persist. These challenges have consequently led to a significant reduction in the efficiency, accuracy and reliability of the system. In this work, an enhanced multi-level descriptors-based mechanism was proposed with threshold value at each level. Fifty (50) persons were enrolled onto the system; both genuine and impostors' identity were verified. Performance of individual modalities were considered in terms of false acceptance rate (FAR), false rejection rate (FRR) and failure to enroll rate (FER) during enrollment and verification. The overall performance of the system stands at 90% with an average verification time of 48 seconds, which certainly show a considerable improvement in the efficiency and reliability of the system over the independent and hybrid methodologies.

Keywords: Multi-level, Fingerprint Recognition, Minutiae and Non-Minutiae Descriptors, Algorithm

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1. INTRODUCTION

Biometric technology has been described as the use of distinctive anatomical and behavioral identifiers such as fingerprints, face, iris, voice, hand geometry etc for automatically recognizing a person (Singh, Kaur and Sardana, (2011). Globally, this technology has emerged as a reliable and highly secure identification and personal verification solutions, more importantly in the wake of heightened concern about security challenges in our world today (Aranuwa, 2014). Notable biometric traits include face, ear, iris, gait, fingerprint, palmprint, voice and so on. But for the purpose of this work, fingerprint recognition is considered. By definition, fingerprint recognition is referred to as the techniques of identifying or verifying a match between human fingerprints (Samayita and Kalyani, 2014). It has been adjudged the most popular and widely used identification method in biometric system as a result of its uniqueness and consistency over time. The system has been a great value in forensic science and criminal investigations, authentication and access control. However, there are number of challenges that recedes the efficiency and accuracy of the system such as degradation and distortions of the trait due to coat variations and impression conditions, non-uniform contact with the scanning devices and conflict features extraction due to the presence of noise. This consequently has led to errors in matching process and large computational requirements. Hence, the need for an enhanced mechanism to overcome the identified challenges.

Generally, biometric recognition process includes image acquisition and preprocessing, feature extraction and matching (Mares et al., 2005). The recognition processes are further categorized into two major stages of enrolment and matching processes. The block diagram in Figure 1, illustrates the basic modes of a generic biometric system.

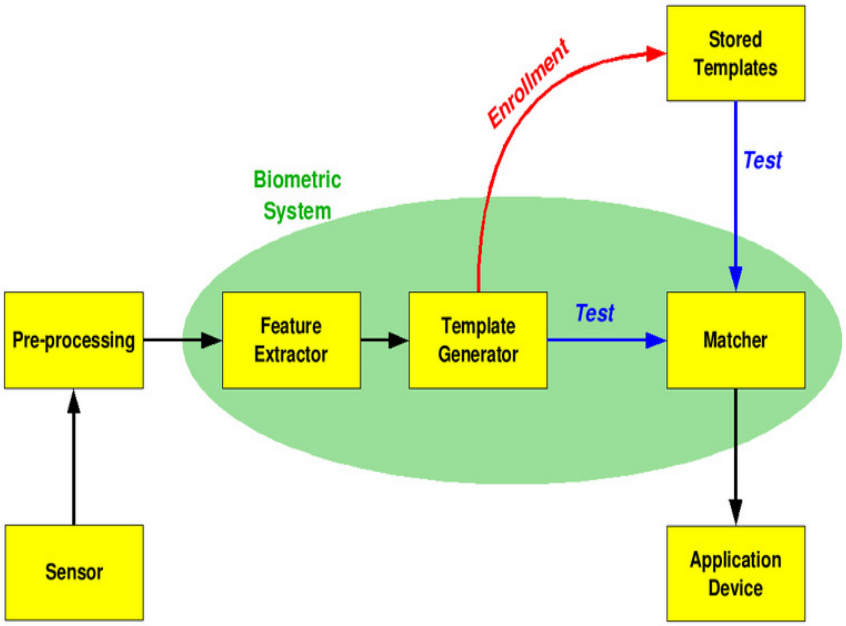

Figure 1 Basic mode of a Biometric System

According to Youssef et al (2010), the image acquisition and preprocessing component is the preparatory and image reading stage. The feature extraction component is responsible for the extraction of salient feature points from both the test and model object mechanisms. It also includes the template generation while the final stage is the matching between test and model images based on the extracted features. These features are used to determine the uniqueness of an individual fingerprint image. Various fingerprint feature extractions have been discussed in the literature by different researchers. But the two main categories for fingerprint descriptors are the minutiae and non-minutiae descriptors.

2. LITERATURE REVIEW

According to Thakkar (2018), a fingerprint is a distinct pattern of ridges and valleys on the finger surface of an individual. By description, a ridge is a single curved segment whereas a valley is the area between two adjacent ridges. The dark areas of the fingerprint as shown in Figure 2 are called the ridges while the white area that exists between them are known as the valleys.

Figure 2: Typical fingerprint image taken through an optical sensor.
Source: (Fingerprint from FVC2002)

A fingerprint image is of three basic patterns as depicted in figure 3 (a-c). We have a loop pattern when one or more ridges enter and exit from the same side in a curvy form of fingerprint. The loop is of two types; the left loop and the right loop. The pattern called Whorl is a ring pattern type of a fingerprint. It could be plain, central pocket, double loop, or accidental. Plain whorls have at least one ridge that makes a complete circuit and an imaginary line from one delta to the other that must touch a whorl ridge. A 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. Double loop is two loops combined to make one whorl. Any other types not in these three categories are called accidentals. The pattern called Arch is a curly ridge that enters from one side and leave out from the other side. They are of two types namely the tented arch and plain arch. (Kaur and Narwal, 2016).

Figure 3: Fingerprint image types
Source: (Kaur and Narwal, 2016).

2.1 Minutiae and non minutiae based descriptors

According to Yang (2012), a descriptor is defined to identify an item with information storage. It is used to descript and represent a fingerprint image for personal identification. Various fingerprint descriptors have been proposed in literature, the two major categories are the minutiae and non-minutiae based. Minutiae based descriptors are the most popularly used algorithms in fingerprint recognition systems. The descriptor uses feature vector extracted from fingerprints as sets of points called minutiae in a multi-dimensional space. This comprises several characteristics such as type, position, orientation, ridge bifurcation and ridge ending on a fingerprint. A minutia of a fingerprint can be determined by calculating the Euclidean distance between the ridge ending and bifurcation. The ridge endings and ridge bifurcations are the most commonly used minutia types since all other types of minutiae are based on a combination of these two types (Thakkar, 2018). Figure 4 shows some of the common minutiae patterns.

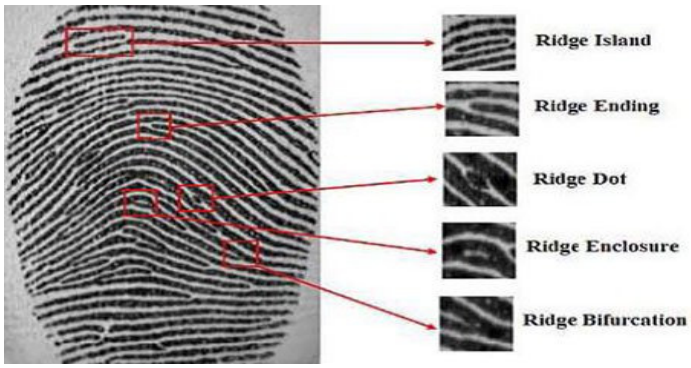

Figure 4: common minutiae patterns.
Source: (Thakkar, 2018)

Despite the wide usage of this descriptor in many large-scale and diverse fingerprint identification applications, the challenges of inability to determine the minutiae points easily and accurately, coupled with errors in matching process that always require a time-consuming pre-processing algorithm prior the matching stage remains an issue (Samayita and Kalyani, 2014).

An important alternative is the non-minutiae which classically is texture based. The texture based fingerprint is of two types, the global and the local. According to James et al, (2009), the local texture analysis has proven to be more effective than global feature analysis. Its descriptor uses properties such as scale, local orientation, frequency, symmetry and isotropy which is usually extracted using the spatial grey level dependence matrix (SGDLM) method. The SGLDM is one of the most popular methods for extracting statistical texture features. In this method, the texture information of the image finds 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 descriptor can extract more rich discriminatory information and abandon the pre-processing process such as binarization and thinning processes (Yang, 2012). Other intrinsic worth of non-minutiae is high accuracy and fast processing speed. Figure 5 show the images of minutiae and texture based representations.

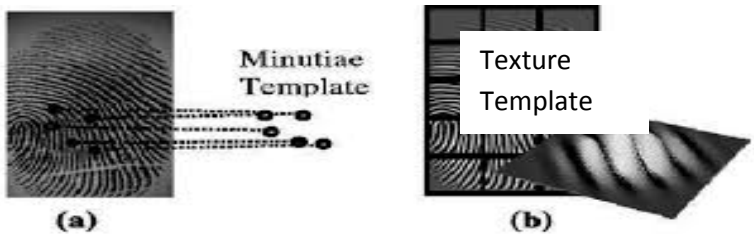

Figure 5 showing (a) Minutiae based fingerprint representation and (b) Texture based fingerprint representation

Researchers at different levels have proposed and used the two representations in different applications independently and by fusion (Manvjeet et al, 2008; Jain, Hong, Pankanti & Bolle, 1997; Zahor, Mir & Rubab, 2011; Zin & Sein, 2012). However, despite the advances in the two methods, the challenges of matching errors and large computational requirements still persist. Therefore, effort in this research work is focused at presenting an enhanced multi-level fingerprint recognition system based on minutiae and texture based descriptors with low computational load to improve efficiency and accuracy of general fingerprint recognition system.

3. MATERIALS AND METHOD

Figure 6 shows the architecture of the multi-level descriptors model. The structural design for the research work is composed of five major modules, namely: the feature extraction, pre-processing and template generation (database), matching and the decision modules.

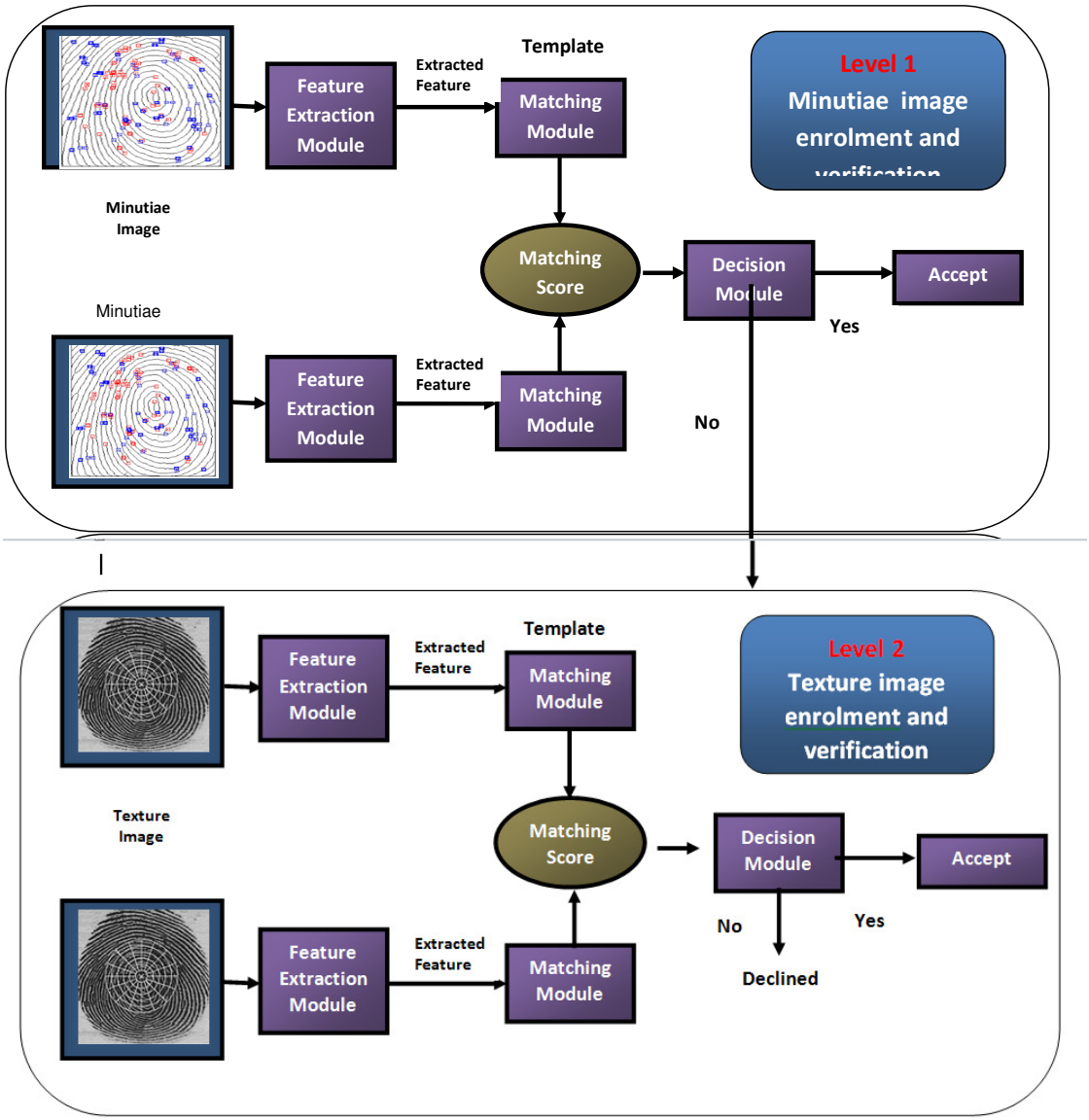

Figure 6: Proposed multi-level fingerprint recognition system model

4. DATA ACQUISITION, PROCESSING AND IMPLEMENTATION

The researcher developed a platform for the fingerprint enrollment and verification process using the proposed model. The platform was successfully used to capture fingerprint images from 50 persons and extracts salient features of both minutiae and texture images using standard enrolment devices with 500 pixels per inch (ppi). Samples of the data captured and extraction platform for the research are shown in Figure 7 and Figure 8 respectively. The feature extraction process entails reading and codifying each of the minutiae and texture features. The captured images were later subjected to image enhancement techniques to improve their qualities and the resulting image was reported in a binary form using Fourier Fingerprint Transform (FTT) method. During enrolment, this feature sets were stored in the database which is referred to as the template while the matching module compares extracted features against the stored template to generate match scores.

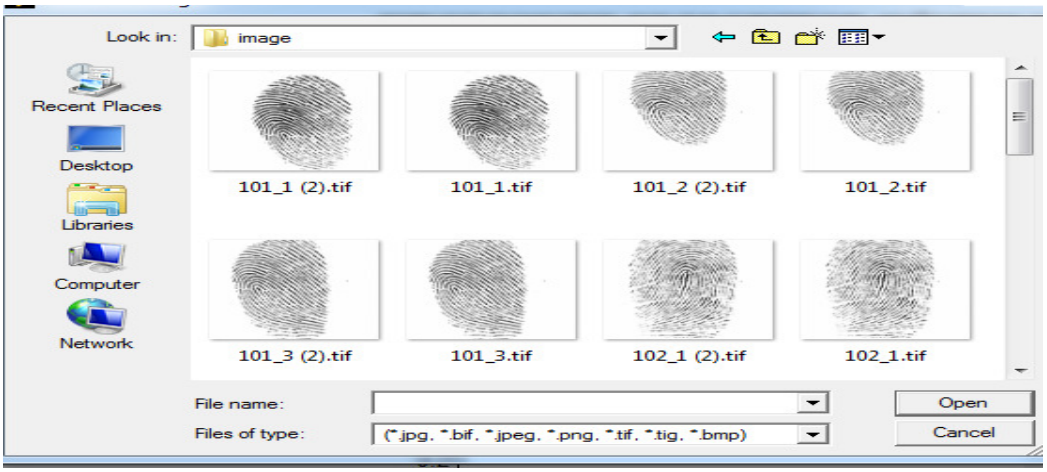

Figure 7: Samples of captured fingerprint images

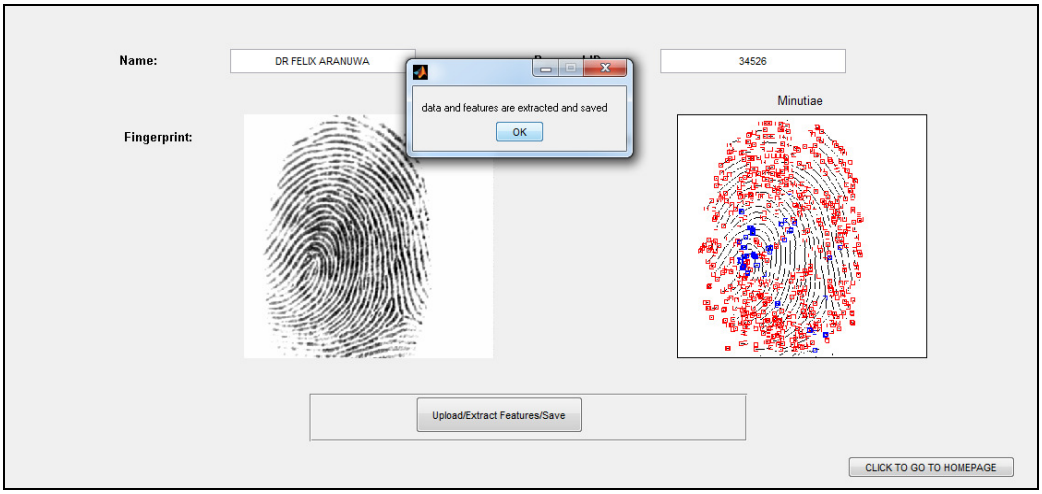

Figure 8: Fingerprint Extraction Platform

4.1 Implementation

Level 1: The minutiae descriptor proposed in this work uses feature vector extracted from fingerprints as sets of points called minutiae in a multi-dimensional space. Each minutia is determined by calculating the Euclidean distance between the ridge ending and bifurcation. Mathematically, Euclidean algorithm is an efficient method for computing the greatest common divisor (GCD) of two numbers. It returns the largest number that divides both of them without leaving a remainder. The Minutiae matching was done by using Rutovitz algorithm based on concept of crossing number which is defined as:

$$C_n\ (P) = (\frac{1}{2})\sum_{i=1}^{8}|P_i - P_{i+1}|$$ ……. *Equation 1*

Where P*i* is the binary pixel value in the neighborhood of P with Pi = (0 or 1) and P1= Pn. 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-1th neighborhood of P. The ridge ending can be found at crossing number C_n (P)>=1 to C_n (P) =2 and bifurcation at crossing number starting from C_n(P)>=1. This model can be represented mathematically as:

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

$$B_N = \sum([C_n(p) \geq 1]) \ldots . (summation\ of\ burfication\ Ending)$$ ……..*Equation 3*

$$T_N = \sqrt{sum((R_N - B_N))^2}$$ …… *Equation 4*

The T_N value is being used for the matching with other minutiae value during authentication.

At level 2, the non-minutiae descriptor uses the texture scale, symmetry and isotropy properties which are usually extracted using the Spatial Grey Level Dependence Matrix (SGDLM) algorithm. SGLDM is a statistical method for constructing co-occurrence matrices to reflect the spatial distribution of gray levels in the region of interest.

SGLDM Algorithm is based on the estimation of the second order conditional probability density defined as:

$$f(\{i, j\,|d, \theta\})$$ ……..*Equation 5.*

The element at location (i, j) of the SGLD matrix signifies the probability that two different resolution cells which are in a specified orientation Θ from the horizontal and specified distance d from each other, will have gray level values i and j respectively.

The estimated value for these probability density functions can thus be written in the form of:

$$\Gamma = \emptyset(d, \theta) = [f([i,j|d, \theta]]$$ …….. *Equation 6*

The decision module uses the match scores to either validate a claimed identity of the user's identity or decides otherwise.

Therefore, the multi-level decision threshold system algorithm is stated as:

If $T_N = \sqrt{sum((R_N - B_N))^2} = 275.5\text{ppi}$, then
Accept,
Else If $P = \emptyset(d,\theta) = [f(\{i,j|d,\theta\}] = 60.5\text{ppi}$, then
Accept,
Else,
Declined.

Table 1 and Table 2 show samples of features extraction/enrolment scores for both minutiae and texture based and matching values with time taken during the matching/verification respectively.
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Table 1: showing samples of features extraction/enrolment scores for both minutiae and texture based

Identity Input number	X location	Y location	Minutiae Matching scores	Non Minutiae Matching scores
1	944	49	9	25
2	1025	23	10	50
3	487	39	4	36
4	846	127	7	48
5	872	31	8	30
6	732	12	7	44
7	126	295	2	23
8	602	468	1	19
9	725	91	6	24
10	628	48	6	29
11	303	383	1	26
12	824	200	6	23
13	421	0	4	46
14	872	31	8	30
“	“	“	“	“
50	974	23	10	35

Table 2: showing the corresponding matching values and time taken for both the minutiae and non-minutiae based algorithm during verification.

Template and Query Image for: Sample Collected	Minutiae based Algorithm		Texture based Algorithm	
	Accuracy (similarity score) 500dpi	Time taken (milliseconds)	Accuracy (similarity score) 500dpi	Time taken (milliseconds)
Sample 1	360	193	82.564	109
Sample 2	303	203	62.812	100
Sample 3	316	185	69.327	107
Sample 4	461	245	74.147	103
Sample 5	347	244	61.619	105
“	“	“	“	“
Sample50	286	167	78.672	104
Mean	275.5	205.8	60.5	104.7

5. RESULTS AND FINDINGS

During implementation, both genuine and impostors were enrolled on the system and verified. During verification, genuine clients were recognized while impostors and those that have their matching scores below the predefined threshold were rejected. The decision to accept or reject identity claim in the multi-level descriptors system was based on a pre-defined decision threshold. The decision threshold value for the minutiae was set at 275.5ppi while that of non minutiae (texture) based was set at 60.5ppi. With the multi-level descriptor mechanism, a matching score below the threshold value at level 1 is passed on to level 2 for further verification, and failure to meet up with the pre-defined threshold also at level 2 will automatically be rejected.

Figure 9 to Figure 11 show few snapshots of the verification processes. In summary, thirty three (33) persons were successfully recognized and authenticated at the level 1, while twelve (12) persons were recognized and accepted at level 2 representing 66% and 24% for the minutiae and non-minutiae descriptors respectively. Five (5) persons were neither recognized at level 1 nor level 2 representing 10% of the population who were impostors. Performance of individual modalities were considered in terms of false acceptance rate (FAR), false rejection rate (FRR) and failure to enroll rate (FER) during enrollment and verification. The overall performance of the system stands at 90% with average verification time at 48 seconds, which certainly show a considerable improvement in accuracy and reliability over the independent and hybrid methodologies.

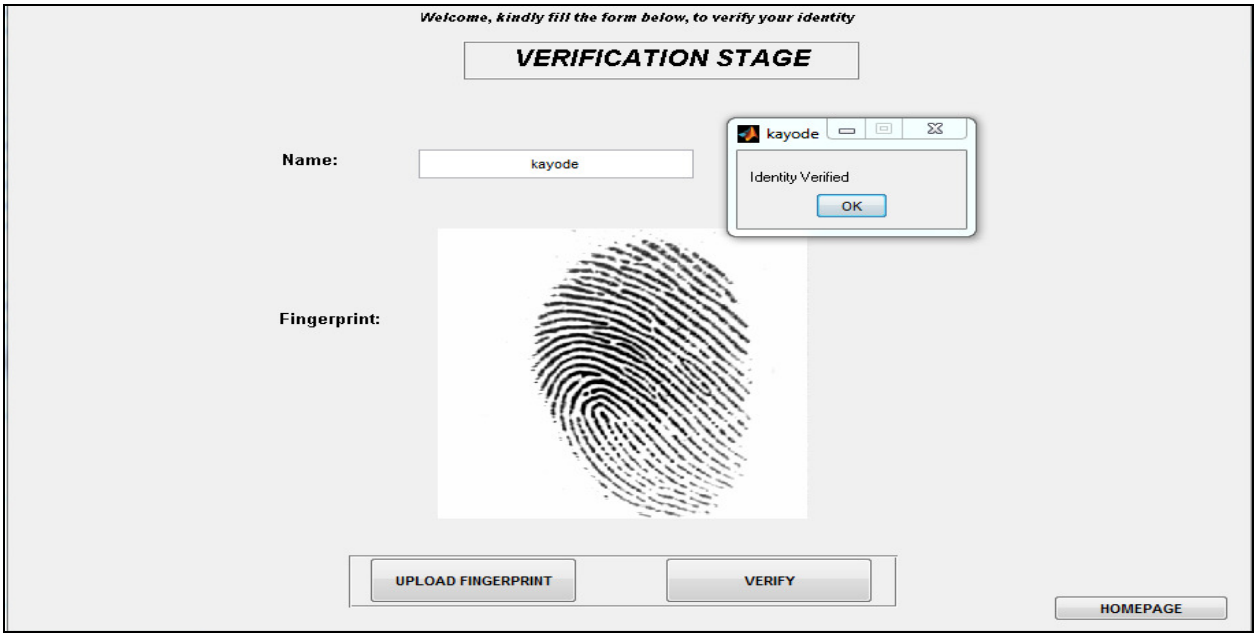

Fig 9: showing sample of user authentication based on the minutiae based extraction at level 1

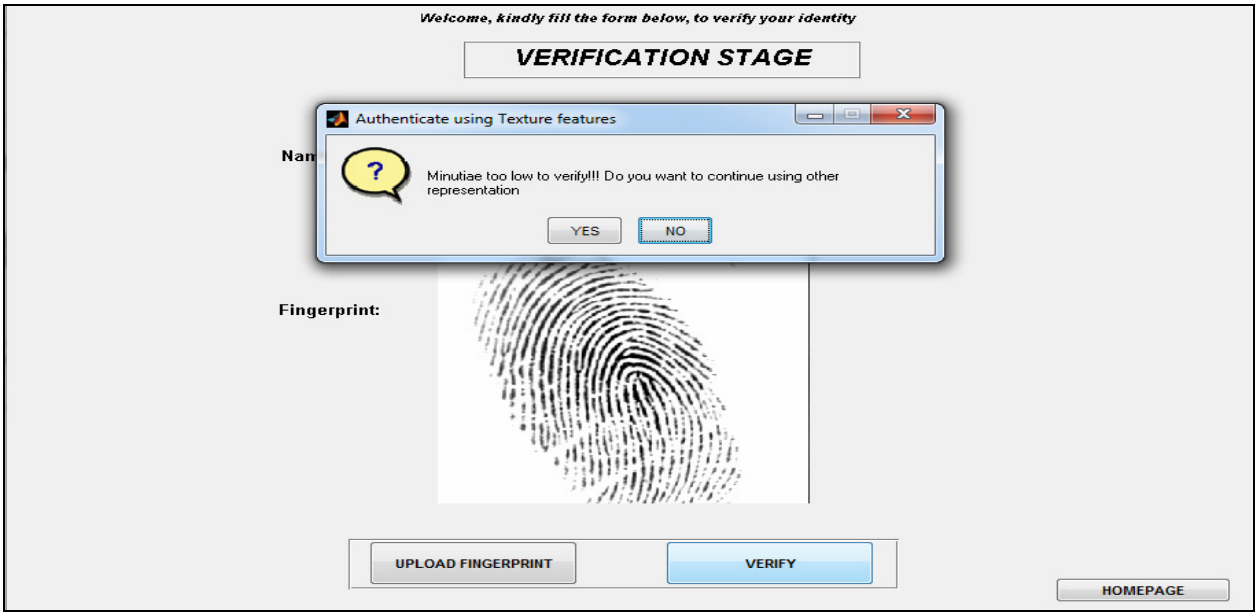

Fig 10: showing sample of rejected fingerprint verification as a result of low matching score.

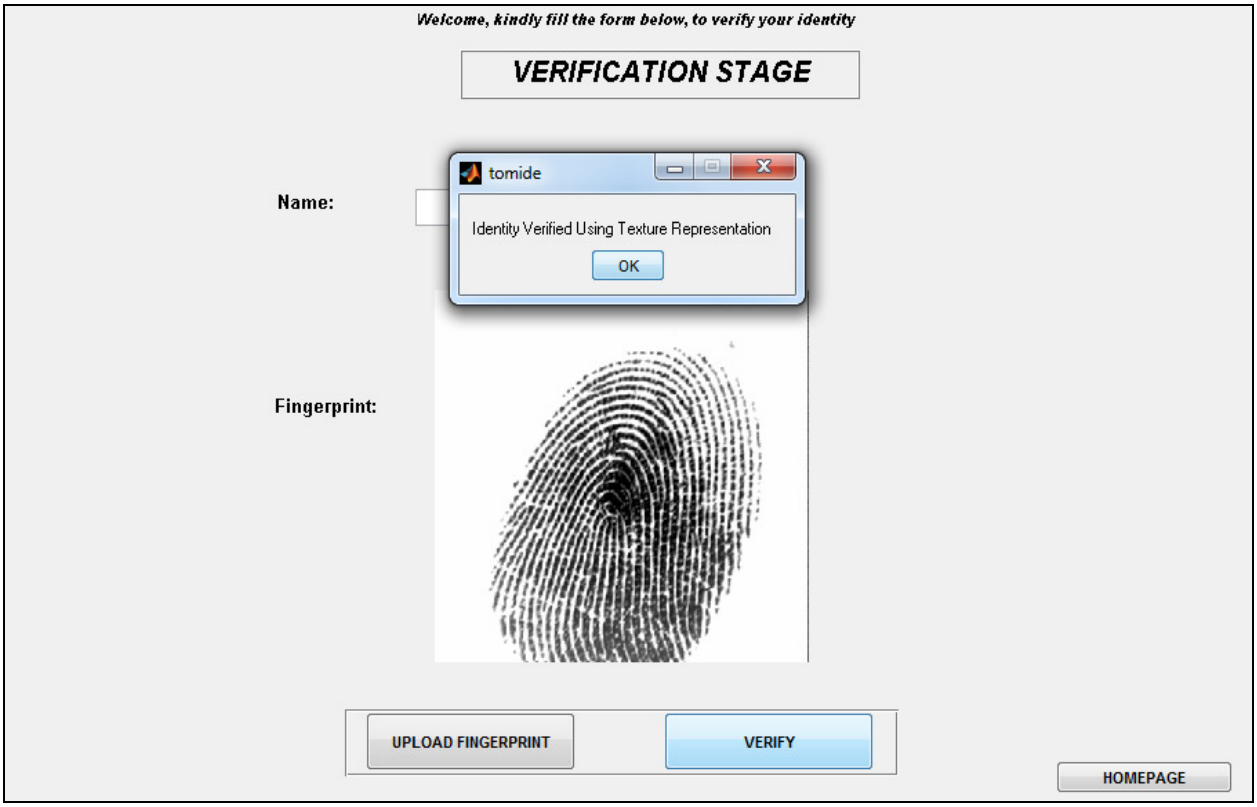

Fig 11: showing sample of user's authentication based on the non-minutiae (texture) extraction at level 2.

6. CONCLUSION

An effort in the research work is focused at presenting a multi-level fingerprint recognition system based on minutiae and non minutiae descriptors. The multi-level mechanism developed was tested and performance of individual modalities were considered in terms of false acceptance rate (FAR), false rejection rate (FRR) and failure to enroll rate (FER) during enrollment and verification. Generally, the overall performance of the system stands at 90%. This experimental results show that the system certainly offers considerable improvements in reliability, accuracy and low computational load with reasonably performance over the independent or hybrid methodologies.

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