

## **Fingerprint Authentication System based on Coalesce Portrayal Approach**

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#### Abstract

#### Keywords:

Fingerprint biometric, Coalesce portrayal, Minutiae, Texture based Single mode Fingerprint identification system is one of the most popularly used biometrics solutions for human identification and authentication as a result of its uniqueness and universality. It has been used in law enforcement and forensics, to identify suspects and victims for over a century. However, in spite of its applications in diverse identification systems, a number of challenges still recedes its effectiveness and efficiency, especially in applications with single mode representation. Study have shown that biometric system that uses a single representation for identification has this predisposition to contend with problems related to distortion, noisy data and error in matching, which often leads to reduction in the accuracy of the system. Therefore, this study considered fingerprint authentication system using coalesce portrayal approach in a single application to improve the efficiency of the system. A biometric system platform was developed and successfully used to capture fingerprint images from 50 persons and extracted salient features of both minutiae and texture of the fingerprint using standard enrolment devices with 500 pixels per inch (ppi). Each minutia was determined by calculating the Euclidean distance between the ridge ending and bifurcation, while the texture based extraction was done using spatial grey level dependence matrix (SGLDM). Genuine and impostors' identity were tested during the enrolment and verification processes. The performance of the system was measured in terms of false acceptance rate (FAR), false rejection rate (FRR), failure to enroll rate (FER). It took the system 58seconds to process a request with performance accuracy of 98% in 3 trials. The results from the implementation when compared with that of unimodal system, showed a better performance in terms of efficiency, accuracy and reliability.

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#### INTRODUCTION

Generally, biometric technology has been described as the use of distinctive anatomical and behavioral identifiers such as fingerprints, face, iris, voice, hand geometry and so on for automatic person's recognition (Singh, Kaur and Sardana, 2011). Globally, this technology has emerged as a reliable and effective method for establishing the identity of a person and controlling access to both physical and spaces, more importantly in the wake of heightened concern about security challenges in our society (Aranuwa, 2016). Meanwhile, experimental studies have shown that a biometric system that uses a single biometric trait/representation for identification or authentication has this tendency to contend with problems related to noisy data and errors in matching (Yadavi et al, 2011; Damousis and Argyropoulos, 2012). Therefore, it is believed that some of the limitations imposed by single representation biometric systems can be overcome and much higher accuracy achieved using multiple representations for establishing identity.

In this work, fingerprint trait is considered, and specifically the coalesce portrayal of the trait in a single application was considered to improve the efficiency of the system. By definition, a fingerprint in its narrow sense is an impression left by the friction ridges of a human finger. Its feature patterns can be used to identify a person. It is one of the most popular and widely used identification methods in biometric recognition system as a result of its uniqueness and universality (Samayita and Kalyani, 2014). Figure 1 shows an image of a fingerprint trait. According to Thakkar (2018), a fingerprint is a distinct outline of ridges and valleys on the finger surface of an individual. A fingerprint ridge is a single curved segment, while a fingerprint valley is the area between two adjacent ridges. The dark area of the fingerprint is called the ridge and the white area that exists between them is known as the valley. Figure 2 show the generic ridges and valley structure of a fingerprint.



Figure 1: Typical fingerprint image taken through an optical sensor. Source: (Fingerprint from FVC2002)



Fig 2: Generic ridges and valleys structure of a fingerprint Source: Manvjeet Kaur et al, (2012)

Fingerprint recognition, also known as dactyloscopy is the process of comparing two instances of friction impressions ridge skin (Ashbaugh, 2013). A fingerprint image is of three basic patterns as depicted in figure 3 (a-c). The loop pattern occurs 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(a-c): Fingerprint image types Source: (Kaur and Narwal, 2016).

#### LITERATURE REVIEW Multiple Biometrics and Representations

Multiple biometrics is a biometric technology that combines many type of biometric information or multiple sources to overcome the limitations of single biometric system (Aranuwa, 2014). Multi-biometric system can be classified into one of the following categories: five multiple sensors, multiple representations, multiple instances, multiple samples and multiple modalities (Akhtar and Affrarid, 2011). But, for the purpose of this work, multiple representation of a fingerprint is considered. In this type of a system, a single biometric input is processed with different feature extraction in order to create templates with different information content. This process is cost effective as it does not necessitate the deployment of new sensors compared to other types of multi-biometric systems.

Various fingerprint feature extractions has been discussed in the literatures, but the two main categories of fingerprint descriptors are the minutiae and texture based portrayal (Thakkar, 2018). The minutiae based portrayal is the most popularly used classifier in fingerprint identification systems. It 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. Figure 4 shows some of the common minutiae patterns.



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

An important alternative is the texture-based (nonminutiae). 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. Texture based descriptor employ 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 texture based feature is high accuracy and fast processing speed. Figure 5 show the imagery of minutiae and texture based templates.



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

Researchers at different levels have proposed and used the two representations in different applications independently (Manvjeet et al, 2008; Zahor, Mir and Rubab, 2011; Zin and Sein, 2012), yet the challenges of efficiency and reliability still persists. Therefore, in this work the duo are combined in a single application to improve the efficiency and reliability of the system.

#### MATERIALS AND METHOD

Figure 6 depicts the architecture of the coalesce portrayal (multiple representations) of the fingerprint identification system designed for this work.



#### Figure 6: Architecture of Fingerprint Authentication System based on minutiae and non-minutiae Representations

The structural design is composed of five major modules. namely: the sensor. feature extraction/matching, database, information fusion, and the decision modules. The decision module uses the threshold score to take a decision. During the implementation, salient features from both minutiae and texture images were extracted from 50 persons using standard enrolment devices with 500 pixels per inch (ppi). The feature extraction process entails reading and codifying each of the minutiae and texture features. The captured images were 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, the minutiae in a multidimensional space were first extracted, and each minutia was determined by calculating the Euclidean distance between the ridge ending and bifurcation. The Euclidean algorithm computes the greatest common divisor (GCD) of the numbers and returns the largest number that divides both of them without leaving a remainder. The formula for this process is stated in equation 1.

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

 $P_i$  is the binary pixel value in the neighborhood of P with  $P_i = (0 \text{ or } 1)$  and  $P_1 = P_n$ . 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-1<sup>th</sup> 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:

$$\begin{split} R_{N} &= \sum ([\mathcal{C}_{n}(p) \geq 2]) \dots (\text{ summation of the ridge ending} \\ \dots \dots Equation 2 \\ B_{N} &= \sum ([\mathcal{C}_{n}(p) \geq 1]) \dots (\text{summation of burfication Ending}) \\ \dots \dots Equation 3 \\ \dots \dots \\ T_{N} &= \sqrt{sum((R_{N} - B_{N}))^{2}} \dots Equation 4 \end{split}$$

The  $T_N$  value is the score for the minutiae representation.

For the texture extraction, the texture scale, symmetry and isotropy properties of the fingerprint images were extracted using 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 any region of interest.

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

# f({i, j|d, 6}\_\_\_\_\_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  $\Theta$  from the horizontal and specified distance d from each other, have gray level values i and j respectively.

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

$$P = \emptyset(d, \theta) = [f(\{i, j | d, \theta\}]_{\dots Equation 6}$$

The fusion of the two scores was done at the measurement level (i.e the confidence level) using the linear summation rule. The threshold value from the duo was computed and used in taking decision during the verification exercise. The fusion equation is stated in equation 7:

*Fus* = (*TN* +*P*) ½.....*Equation* 7

Where, **TN** is the minutiae score and, P is the texture based score.

The screenshot in Figure 7 shows the homepage of the fingerprint identification system during implementation.



Fig 7: Homepage of the Multiple Representations System

Figure 8 and Figure 9 showed the samples of data captured and feature extraction platform respectively.



Figure 8: Samples of captured fingerprint images in the database



Figure 9: Fingerprint Feature Extraction Platform

#### **RESULTS AND FINDINGS**

The decision to accept or reject identity claim in the verification process was based on a pre-defined decision threshold value of 18.1. During verification, both genuine and impostors' identity were tested. Genuine clients were recognized while impostor was rejected. Forty-nine (49) persons representing 98% were successfully recognized and authenticated. One (1) person representing 2% could not be enrolled. The impostor was deliberately introduced, and which was rightly rejected. It took the system an average of 58 seconds to process a request in 3 trials. Figure 10 and Figure 11 show the snapshots of the verification acceptance and rejection respectively.

#### PERFORMANCE EVALUATION

An important issue for the adoption of biometric technologies is to establish the performance of individual biometric modalities and overall systems in a credible and objective way. One performance parameter is the measure of the errors in biometric system which is usually tested in terms of false acceptance rate (FAR), false rejection rate (FRR) and failure to enroll rate (FER) during enrollment and verification.

The performance evaluation of the verification system was computed using equation (8) - (10) as reported below:

time taken to identify an individual during verification processes; an average of 58s was reported. Results from this processes show that the approach was found to be more robust when compared with other system in the domain in terms of accuracy and reliability.

Figure 10 and Figure 11 show samples of user authentication and rejection respectively during verification.



Figure 10: Sample of user's authentication during verification



Fig 11: Sample of authentication failure or rejection during verification.

 Table 1: showing the matching threshold values and time taken during verification

| Template and     | System Performance |           |
|------------------|--------------------|-----------|
| Query Image for: | Accuracy           | Time      |
| Sample Collected | (Threshold         | taken     |
|                  | value)             | (seconds) |
| Sample 1         | 18.0               | 61        |
| Sample 2         | 18.6               | 58        |
| Sample 3         | 18.1               | 60        |
| Sample 4         | 18.0               | 57        |
| Sample 5         | 18.2               | 59        |
| "                | "                  | "         |
|                  |                    |           |
| Sample50         | 18.7               | 58        |
| Mean             | 18.1               | 58s       |

#### CONCLUSION

The research work considered coalesce portrayal of fingerprint in a single application to improve the efficiency of fingerprint identification system using minutiae and texture feature representations. A system platform was developed for this purpose, and was used to capture fingerprint images from 50 persons and handle the biometric processes successfully. The performance of the system was evaluated in terms of accuracy and time taken during enrolment and verification processes. Results from

the exercise showed that the new approach was found to be more robust than the single mode representation in terms of efficiency and reliability. With this presentation, the research work has met its objectives; however in the future work, bigger database and global matching algorithm is proposed.

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