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**CANCELLABLE BIOMETRIC  
USING MATRIX APPROACHES**

**DOCTOR OF PHILOSOPHY**

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## SCHOOL OF ELECTRICAL AND ELECTRONIC ENGINEERING

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# Abstract

Cancellable biometrics endeavour to hide the appearance of a biometric image into a transformed template which prevents the outsider from recognising whom the biometric belongs to. Current research into cancellable biometric methodologies concentrates on the details of biometric traits. This approach has a drawback which cannot possibly be implemented with other biometric technology.

To address this problem, this thesis contributes to development of a novel concept for the feature transformation of biometric technology, especially for fingerprints, by utilizing several matrix operations to provide an alternative algorithm in order to produce multi-implementation of the cancellable system. The matrix operations generate the feature element of the input fingerprint image in an irrevocable form of output fingerprint template by ignoring the type of biometric traits unique to fingerprints; thus, the cancellable algorithm can be implemented in different biometrics technologies. The implementation offers a new concept in generating a cancellable template by considering a sequential procedure for the fingerprint processing, in order to allow the authentication process to succeed in authenticating an enquired input. For example, a region of interest (RoI) step is required to provide a square form input to support the system working in a matrix domain. Meanwhile, the input fingerprints are mostly in rectangular form.

This thesis contributes a new approach to selecting a certain area of a fingerprint by utilizing the density of ridge frequency and orientation. The implementation of these two enhancement steps reduces the excision process of this significant region of the fingerprint by avoiding the involvement of a non-feature area. Meanwhile, to avoid obtaining an unclassified fingerprint, this thesis offers a new approach to the fingerprint image classification process entailing three requirements in classifying the fingerprint: the core point and its number, ridge frequency, and ridge direction; whilst the tented arch (TA) is only an additional requirement. The proposed idea increases both the percentage accuracy in classifying fingerprints and time consuming of the system. For Example, the accuracy of the fingerprint classification improves from less than 41 per cent of the fingerprint to 86.48 per cent in average for all of databases.

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and the Time Taken by the Process

# Abbreviations

DNA	Deoxyribonucleic Acid
DC	Direct Current
ID	Identity
PIN	Personal Identification Number
ERO	Elementary Row Operation
KP	Kronecker Product Operation
RoI	Region of Interest
TA	Tented Arch
FAR	False Accept Rates
FRR	False Reject Rates
EER	Equal Error Rate
MRF	Markov Random Field
DC	Direction of Curvature
GR	Geometry of Region
AFIS	Automatic Fingerprint Identification System
FVC	Fingerprint Verification Competition
DB	Database
BRC	Biometrics Research Centre
INV	Inverse Matrix Operation
CN	Crossing Number
GAR	Genuine Accepted Rate
CPU	Central Processing Unit
GHz	Giga Hertz

RAM	Random Access Memory
MATLAB	Matrix Laboratory
dpi	Dot per Inch

# List of Publications

1. R. Mukhaiyar, S. S. Dlay, and W. L. Woo, “Alternative Approach in Generating Cancellable Biometric by using Matrices Operations”, In *the Proceedings of the 56<sup>th</sup> International Symposium ELMAR-2014*, pp. 163-166, Zadar, Croatia, Sept. 10-12, 2014.
2. R. Mukhaiyar, S. S. Dlay, and W. L. Woo, “Generating Cancellable Fingerprint using Matrices Operations and Its Fingerprint Processing Requirements”, Journal Submission, 2014.

# Chapter 1

## 1. Introduction

### 1.1. Biometrics

Biometrics is a method of identifying human uniqueness based on one or several features of either physical or behavioural characteristics. The physical characteristics relate to the human body, such as fingerprints, the face, shape of the hand or palm, iris, retina, DNA, or even human smell. Conversely, behavioural characteristics relate to human features, for instance sound, typing rhythm, or the way a person walks. These characteristics are used to identify humans based on the basic concepts of uniqueness, permanence, and collectivity.

Thus, the basic idea of biometric science is to use part of the human body as the key or sign to obtain detailed information. This is either from the person whose part body part is being used, or from someone who has a certain relationship with them. In computing science, biometrics is specifically used as a requirement in managing private access and also in controlling access given to an individual. In addition, it can also be used to identify a person in a group which is under supervision.

One of the main biometric technologies that has been studied in detail is fingerprints. Fingerprints can be defined as ‘a trace or an imprint of friction of contraction in most or all of the surface of the human fingers’. The friction of contraction can be found on the palm of one’s hand, fingers and toes, and on the skin of one’s foot. It consists of one, or more of contraction unit that is connected to the imprint of the skin. This contraction is also known as ‘dermal contraction’.

Nowadays, the acquisition process of a fingerprint from its source is conducted through direct fingerprint reading, also known as live fingerprint reader. This technology relies on the principles of thermal and optical as well as silicon and ultrasonic sensing [1], [2], [3] and is mostly used to read the fingerprint. It is based on the concept of changes to the reflection in the area where a person's finger touches the surface of the reader. All readers that use optical technology consist of a source and a light sensor, and moreover a source of specific reflection that can change a reflection if pressure occurs. Several of the type of readers are equipped with processing equipment and a chip memory. The sensor used in this technology is based on DC capacitance from fingers, and contain a layout of a capacitor with a square shape that is implanted on the silicon chip. One side of the capacitor's plate is on the finger, while the other side, which contains a small area made from metal, is on the surface of the chip, so that the finger is opposite the chip's surface.

Another type of fingerprint reader technology is based on ultrasound, however, this is less frequently used [4]. The initial concept of this technology is to use the ultrasound to observe the surface of the pictures. The ultrasonic sensor will start moving and reading the entire fingers for one or two seconds, as soon as the user place the fingers on a piece of glass that is on the reader. The results will be saved in a particular unit in a database. This database will be used when the application system for fingers requires confirmation by matching the database with the fingers. If the fingers are recognized as one of the collection in the database, the application system will accept them as the owner of the fingerprint. Otherwise the application will state that it is an impostor. This process is known as the authentication process of the fingerprint, and furthermore is also called the process of matching fingerprints.

Fingerprint matching techniques can be classified into two categories: minutiae-based and correlation-based [5]. In the minutiae-based technique, the initial concept of matching the fingerprint is achieved by obtaining the minutiae before arranging the placement, and then

ascertaining the connection between the minutiae and the fingers. Conversely, the correlation based technique requires the exact location during the registration process. In addition, it is also affected by the rotation and movement of the image [3], [6], [7], [8].

In this research, matrix operations are the main rule utilized in generating the cancellable fingerprint template. The matrix operations are used to produce a transformed template of fingerprint which is irrevocable to the original image of fingerprint. This irrevocability factor is needed to protect the information of fingerprint to be compromised by impostor. Initially, if a fingerprint is being processed in the matrix domain, then each pixel of the image describes what the image is. This means that no noise is allowed as a part of the image because the existence of noise may add specific information to the fingerprint feature. In relation to the cancellable fingerprint, at the end of this process is the authentication step, where even a small amount of noise will significantly affect the quality of the cancellable feature and result in low precision in subsequent verification.

Thus, an early process to be accomplished in establishing a fingerprint is the enhancement process. The result of this process will provide a fingerprint feature with the precise value of all of its information, so that when it is mathematically processed with matrices operations, there will be no unnecessary values contained within it. The result of these operations will be the input of the cancellable system that is going to be created.

## 1.2. Cancellable Biometrics

The advances in information technology and increases in security concerns have encouraged the rapid development of automatic personal identification systems in biometrics. Biometric technology that accurately and automatically identifies a person based on their

physical and behavioural distinctions is considered to be crucial, given the need for something reliable and capable of distinguishing whether the biometric owner is real or bogus [9]. This technology is more preeminent than the token-based method or even other knowledge-based methods which are based on traditional concepts, given that biometric technology offers a particularly comfortable and secure process for its users.

Proving a person's uniqueness using biometric technology is reliable, as human physical characteristics are very difficult to imitate or falsify, compared with other methods that use security codes and passwords, but requires a significant amount of important memory. Biometric authentication can be located in various applications, such as in network access and the workplace, log-on applications, data protection, the long distance access of resources, website network security, e-government and e-commerce. Furthermore, biometric technology will be needed to provide electronic banking services, as well as other financial and investment transactions. In addition, retail sales, law enforcement, health and social services also require this technology. It is expected to play an important role in clarifying a person's validity in larger scale trading networks that require authentication and protection for its applications.

The implementation of biometric technology, whether on its own or combined with other technologies such as smart cards, digital signatures and encrypted biometric keys, has already been implemented in many areas. Thus, personal authentication through biometric technology presents a new challenge in protecting personal data, which cannot be established using traditional authentication methods. Moreover, users' biometric data relating to health and personal information will not be able to be changed, to be processed, or even illegally distributed without the approval of eligible users [10], because during the cross-matching process the system will also detect the invalidity of subjects that are registered by the eligible users. Besides this if someone's biometric data is stolen by ineligible users, the biometric

security system will be able to verify the identity of the impostor. This is possible since the biometric data is permanent and interconnected with the data owner. Nevertheless, it is undeniable that someone will lose his/her privacy as a consequence of using biometric data.

Due to a number of issues related to users' privacy and security, many recent studies have attempted to find a method to protect biometric systems from the possibility of misuse by improving certain points that are considered to be deficient [11]. The security in this method will have to be able to improve its security system, while efficiently running the matching process and ensuring that it continues to identify appropriate biometric data. The fact that biometric data is permanent and unique, as it is not owned by two or more persons, means that offences against one's personal data is less likely to happen, as in a traditional system where a person's identification, such as ID and PIN (personal identification number) can be cancelled and remade.

Another approach proposed to protect biometric data is the biometric cryptosystem [12]. This technology embeds key information onto the feature of biometrics as an additional information about it. This information could not be revealed without a successful authentication procedure. However, this technology has drawbacks related to unstable recognition performance caused by the unreliable production of the key information [13].

With regards to sharing personal biometric data in public, for instance with commercial companies, enforcement agencies, and government agencies, security and privacy systems in biometric technology have been vastly improved by implementing cancellable biometric technology [13], [14]. This is based on the fact that biometric data do not vary much over time (permanence) and are very rarely shared by two people (uniqueness) where privacy violations could occur if biometrics are misused or stolen. Traditional methods for identifying people, for example, ID and personal identification numbers (PINs), can be

cancelled and reissued if the above privacy issues are compromised; however, this is not possible with biometric data. Furthermore, there are privacy concerns about sharing biometric data with commercial companies and law enforcement or government agencies.

Cancellable biometric technology uses biometric data that is intentionally transformed instead of using the original biometric data in order to identify a person. The initial concept of cancellable biometrics is that the system or the eligible user can automatically nullify the registered data if his/her biometric data is being misused. The data in the cancellable biometrics has to be different from the initial data and cannot be easily reconverted into its original version, although the method of prior data transformation is known, and, moreover, that the transformed version of the original data has been submitted. The original data can be transformed into various types of data; however, the quality of the data does not decrease compared to its fundamental version.

These advantages have motivated researchers in the biometric security field to find a new and enhanced approach to generating a cancellable biometric template. A consideration of the various possibilities to produce an algorithm for the cancellable biometric is a principle reason for us to discuss the cancellable technology in this thesis.

### 1.3. Thesis Aims and Objectives

The main aim of this work is to produce a novel approach to the generation of cancellable biometric features, particularly in fingerprint technology, by providing an alternative method to produce a cancellable template that is able to be implemented not only using one specific biometric technology. This aim can only be successfully achieved by first

understanding the basic requirements of a cancellable fingerprint. The objectives of these requirements are:

- Produce a novel approach in generating cancellable biometric features, particularly in fingerprint technology.
- Provide an alternative method to produce a cancellable template that is able to be implemented not only for fingerprint technology but for another biometric technologies as well.
- Provide all supporting fingerprint process algorithms, for instance fingerprint enhancement and core-point identification to produce a dependable cancellable fingerprint template.

## 1.4. Contributions

With current cancellable biometric methodologies, research is focusing onto the details of biometric traits. Hence, the resulting algorithms cannot possibly be implemented in other biometric technologies. For example, a cancellable fingerprint using the rotation and orientation of the minutiae approach is not appropriate for generating cancellable face, iris, or retina.

- Based on this disadvantage, a novel concept of utilizing matrix operations is introduced in this thesis, to give an alternative algorithm which can produce a multi-implementation cancellable biometric. The methodology developed in this thesis is not limited to the proposed fingerprint only, as it is also able to be used for other biometric technologies, for instance face, or palmprint.

- This research proposes a new concept with the aim of producing a cancellable template. The concept requires a sequential procedure to guarantee that an established and a queried biometric feature are compatible with an accepted one and incompatible with a rejected one. This framework makes any applicant of this proposed approach to be able to analyse less performance of the system.
- In generating the cancellable template, several requirements should be provided as an input. One of the requirements is an input image form that is improved in a square form shape and furthermore, a region of interest (RoI) algorithm is needed to select a particular area of the fingerprint. In this thesis, a new method is applied by utilizing the density of ridge-frequency and –orientation. The implementation of these two enhancement steps reduces the excision of the important region of the fingerprint and avoids involving the featureless area.
- To avoid obtaining an un-classified fingerprint, there are three principal requirements of the proposed fingerprint classification image process: the core point and its number, ridge frequency, and ridge direction; whilst the tented arch (TA) is only an additional requirement. The proposed idea enhances the percentage accuracy in classifying the fingerprint.

## 1.5. Thesis Outline

The thesis is organised into seven chapters. The first chapter presents an introduction to this thesis and describes what biometrics and cancellable biometrics. This is followed by the aims and objectives, thesis methodology and its contributions. In addition, the outline of the thesis is also described in detail to illustrate its contents.

Chapter 2 focuses on producing cancellable biometrics along with the requirements needed to achieve a reliable cancellable template, such as being non-invertible and re-issuing and the authentication of performance. The existing cancellable biometric approaches are considered so as to illustrate the uniqueness of the algorithm proposed in this thesis. Nevertheless, the matrix operations used in this research are discussed as well.

Chapter 3 discusses fingerprints as a biometric technology requiring several methods in order to produce a reliable cancellable template; such as, fingerprint enhancement, core-point identification, region of interest, fingerprint classification, minutiae extraction and fingerprint authentication.

Chapter 4 presents an innovative approach to generating a cancellable fingerprint template using several matrix operations. A description of each operation is explained algebraically to illustrate how the operation works. Moreover, the methodology for this exclusive approach will be introduced along with results that indicate that the method is reliable enough to generate a cancellable template.

Chapter 5 analyses the requirements regarding pre-processing, core point identification, and region of interest, fingerprint classification, and minutiae extraction, in order to support this distinctive approach, which produces a dependable cancellable biometric methodology.

Chapter 6 focuses on a performance evaluation of the approaches discussed in chapters 4 and 5, such as the evaluation of error rates, time taken and the requirements for matrix operations.

Chapter 7 presents the overall conclusions of the thesis and moreover provides some guidance for future work that has emerged from this research.

# Chapter 2

## 2. Cancellable Biometrics

### 2.1. Introduction

The use of representations of identity such as passwords and ID cards is no longer sufficient, as these can easily be shared or compromised. The security requirements in an authentication system based on biometric technologies have to be the benchmark of the system, as its characteristics will be permanently associated with the eligible user and cannot be cancelled or withdrawn when used inappropriately. Someone's biometric characteristics cannot easily be replaced. So if an impostor misuses it, the data will be lost forever. As a result, there is a possibility that the user will lose all access to the application using that particular biometric data. In order to overcome this problem, the susceptibility of the biometric system needs to be systematically identified and recognized [15], [16]. Thus, protecting biometric information has become one of the main concerns, as well as a major challenge to researchers, in this field.

Cancellable biometric is a concept where its biometric template is protected by combining both the security system and replacement features in the biometric system. The main idea of this system is the transformation of the cancellable biometric and the changing of all images and features before proceeding to the matching process, whilst still maintaining the natural characteristics of the cancellable scheme. An appropriate cancellable biometric system has to have the following standards: to be distinctive and reusable, and with unidirectional transformation and performance [17].

The transformation process implemented in various biometric technologies has several functions such as: face identification [18], [19], [20], [21], signature identification [22], [23], iris identification [24], [25], [26], [27], and voice identification [28], [29]. Many recent papers consider that fingerprints are one of the technologies that are being widely discussed for use in biometric systems [30], [31], [32], [33] & [34].

Three types of transformation have been recommended for implementation [30] with fingerprint images: Cartesian transformation, polar transformation and image folding transformation. However, the former two types have a disadvantage in relation to the boundary issue. If the original minutiae point is away from its boundary and then divides the area of the feature, as a result of minor distortion to the image alignment or if the original fingerprint image is damaged, then the transformed version of the minutiae points will be placed far from where it is supposed to be. Meanwhile, the third method relates to the functional use of smoothing a local value to flip a fingerprint feature over the space.

Local smoothing function has been used to create a cancellable fingerprint template by maintaining the original geometric connection (rotation and movement) between the registered template and the questionable template after the transformation process is conducted [33]. Therefore, the result from the template transformation can be used to identify a person without requesting the alignment of the image fingerprint that is being used as an input. However, this security method is insufficient as protection for biometric data. For example, an impostor might narrow down the candidates of the original minutiae design based on limitations in the orientation continuity of the minutiae feature and the local smoothing process of the transformation function.

Several investigations have been conducted regarding this issue. For instance, the conversion of a fingerprint into a binary-string area is based on its minutiae series [34]. The

representations of binary numbers are transformed into an anonymous representation using a unique personal key. According to the author, not only is the transformation non-invertible, but also when it is misused by someone else, the template will disappear and can be renewed by entering a different key. One of the advantages of this representation is that existing methods, for instance bio-hashing could be implemented.

Alternatively, a secure method has been introduced to produce a template of a cancellable fingerprint [35]. This method extracts a local image of the fingerprint filled with minutiae in small pieces and subsequently transforms them into projection matrices without changing the space between each minutia in those small pieces. However, the disadvantage of this method is the poor accuracy of the transformation results. It can be noted that [36] presents an idea in constructing a cancellable biometric system and secure sketches, in order to protect the privacy of the biometric template while supervising the matching process between the protected and referenced data. The standard process in cancellable biometrics is to perform a transformation to create an unchangeable image and to produce a matching process for those transformed images. In this technique a correction system is used on the sketches which can be secured from the cancellable biometric system, resulting in a procedure that supervises the appropriate matching process.

The geometric transformation system of the minutiae position has also been proposed to create a template of cancellable fingerprints [37], which is useful in an alignment process. In order to create a template of the cancellable fingerprint, a supervising parameter over the encryption of minutiae features is conducted on the surrounding area of minutiae. Subsequently, all the encrypted minutiae will be superimposed to form a protected template. The parameters used to control minutiae encryption are created from the arranged minutiae geometric. Compared with the parameters where the algorithms for the cancellable templates

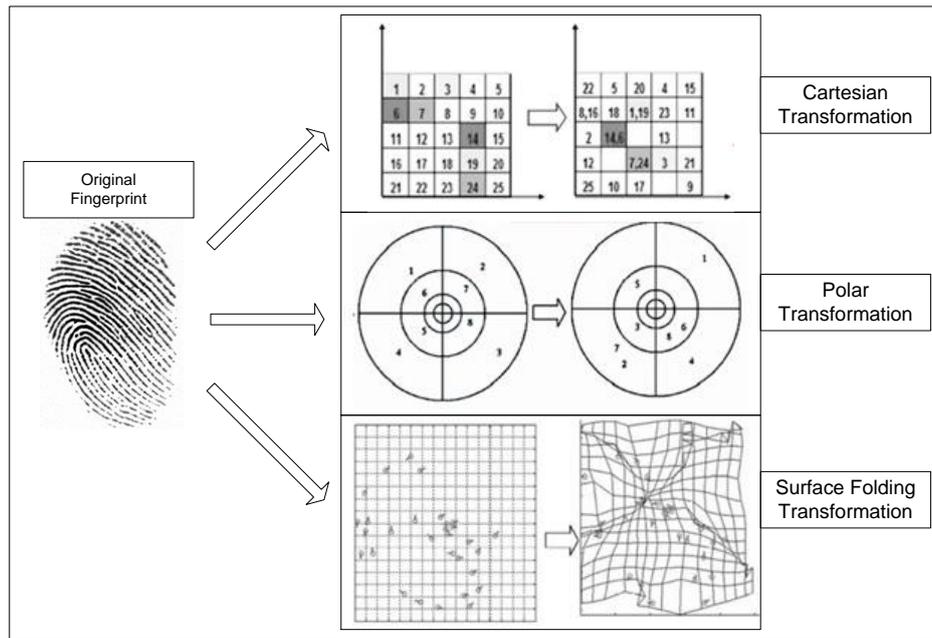
use the information from the minutiae that have to be encrypted, this minutiae encryption can guarantee the solidity of the non-invertibility concept.

## 2.2. The Non-Invertible Issue

In non-invertible transformation systems, a function, for example  $B$ , is designed to transform the original biometric image into a new image within the scope of the domain feature or signal. The  $B$  will serve as a key factor in protecting the cancellable template, as well as determining if the template is non-invertible, reusable and variable. In view of the fact that function  $B$  is not directly related to the original biometric image, then function  $B$  does not have to be kept confidential.

This non-invertible transformation has been used where the fingerprint data is transformed by the order of the three functions of non-invertible transformation [30]. As shown in Figure 2.1, the three transformation functions are based on the Cartesian polar concept and the surface folding transformation of the existing minutiae.

In general, the three transformation functions in Figure 2.1 enable more than one minutia to be mapped onto the same points within the same transformation domain. This is also known as many-to-one mapping. For example, two or more cells can be mapped into a single cell in the Cartesian transformation, so that when the impostor discovers the key and the transformation between the cells, the owner of the original cell will not be discovered, as each minutia can refer to one of the cells at large. Therefore, this method provides certainty over the resulting templates of non-invertible transformation.



**Figure 2.1. Cancellable Templates from Different Transforms (adopted from [30])**

However, it has been argued [38] that the transformation and the choice of parameters in this approach might decrease or even abolish the characteristic of many-to-one mapping on which the non-invertible functions will depend, which will result in the reversion of the original biometric feature. It has been shown [39] that the surface folding transformation can be reversed to its original form if two transformed original templates are compromised.

A further study [40], the author presents a method of hashing minutiae information for fingerprints and conducted the matching process in a new domain. Computationally, it is quite complicated to reconstruct the original features because of the hashing value, as the results from this method have a one way characteristic of transformation. Meanwhile, a geometric transformation has been proposed [41] to create a key-dependent non-invertible cancellable template for minutiae fingerprints. In this method the first factor to determine is the core-point and where a line passes over that particular core-point. However, since the

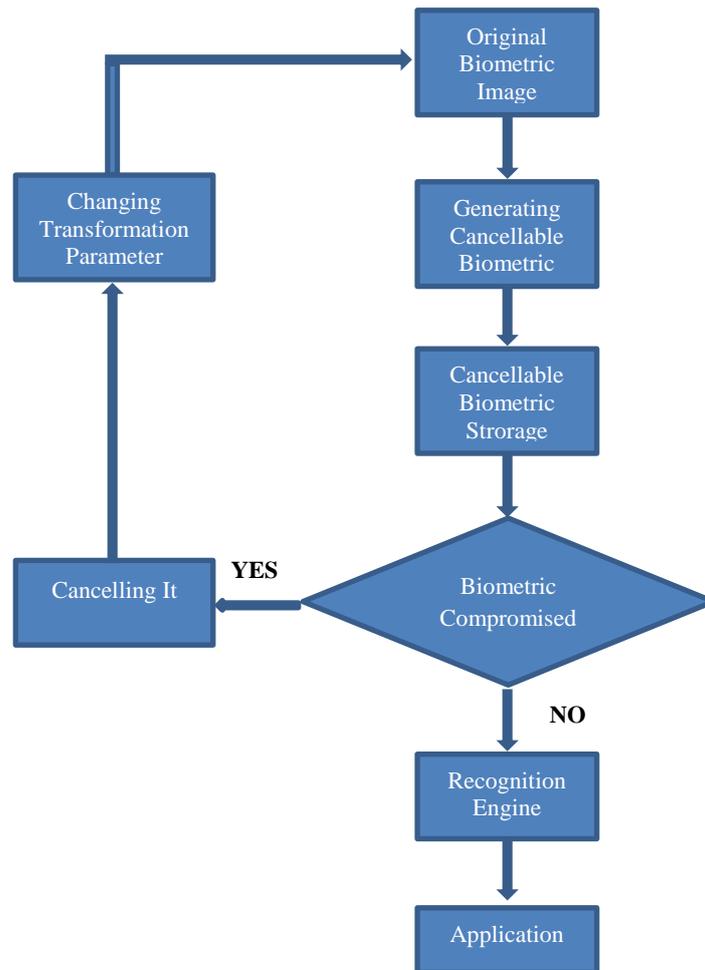
minutiae that are above the line reflect symmetrically below, this means that the template of the transformation contains some information from its original template.

Cancellable biometrics offers a solution to protect the user's privacy, as the client will never be identified in the authentication process. This will guarantee that the protection of template can be obtained at a feature level by using support from data in a non-invertible transformation [42].

### 2.3. Re-Issuing

Biometrics automatically identifies and verifies someone based on his/her physical, biological, and/or behavioural characteristics. Compared with traditional identification and verification methods, biometrics is not only considered to be comfortable for its users, but also minimizes the number of impostors and is more secure. Biometrics is also associated into: the security system, through intelligent, and a security forces.

Nevertheless, there are several concerns related to the application of biometrics in everyday life, such as security and privacy issues, along with the question of ensuring that it is standardized. The principal concern is the issues that relate to biometric data security. Unlike traditional identification methods, it is difficult to re-issue a person's biometric data. Therefore, cancellable biometrics allows the system to re-issue the user's biometric data by mixing up the biometric features before continuing to the matching process. The mixing parameters can easily be changed to prevent the data being misused. Figure 2.2 demonstrates how a system of cancellable biometrics re-issues the original biometric image.



**Figure 2.2. Re-Issuing in Cancellable Biometrics**

## 2.4. Accuracy Performance

A problem will occur in the biometric authentication system when the data associated with the biometric features is misused. Unlike with biometrics system, physical authentication systems using a form of token such as a key or an ID can easily be cancelled or replaced with a new token, whenever the token is lost or misused. Conversely, it is not possible to change or to replace the data in a biometric system.

The performance evaluation of systems based on the biometric authentication is a vital issue. Authentication systems will run the process by comparing the live biometric data from the owner, which can belong to the owner or to others, with the original reference template made by the system during the registration procedure. Matching the biometric information entails calculating the degree of similarity between the live data in question and the registered reference template. The results from this comparison process will be scored.

The false acceptance rate (FAR) and false rejection rate (FRR) are the important basic performance measures of the matching process. The values of the rates for a threshold of tolerance, however, combine levels of FAR and FRR in considering the security and convenience of a biometric-based authentication system. In practice, the most challenging aspect is to obtain a zero score for FAR and FRR. If the FAR score is higher, the system will be more likely to recognize impostor data as genuine. If the FRR result is high the live data of the owner will be recognized as an impostor, and vice versa. The impact of rejection in a biometric system therefore becomes the main focus of discussion, and another index of performance has been introduced where the point of FAR and FRR will be equal [43]. This point is known as the equal error rate (EER), and a system will be considered as perfect if the EER score is zero.

## 2.5. Matrix Operations

The objectives of this research are to produce a cancellable template for fingerprints based on the similarity between the non-invertible need for the fingerprint template in the cancellable system to be non-invertible and a non-invertible matrix in the matrices operations. A template can be categorized as a cancellable template when it is non-invertible

to the original image. This also applies to the matrices. The matrices cannot be inverted when satisfying three conditions. Firstly, there is at least one zero row. Subsequently, there is a row that is a multiple of another row; and finally, the matrix form is not a square.

The first requirement can be achieved by using an elementary row operation (ERO), where a selected row is multiplied by zero. Meanwhile, for the next requirement, it is rare to find a row in the image system which is a multiple of another row; hence, it can be created using ERO.

Furthermore, to ensure that the obtained cancellable matrix is completely masked and to be able to meet the final requirement of the non-invertible matrix, each element of the transformed matrix is multiplied by an arbitrary matrix/element in this research. This process is called the Kronecker product or tensor product operation. By using this process, the outcome comprises those matrices, and contains more numerous elements and an adjustable matrix form (whether a rectangle or square matrix).

### 2.5.1. Elementary Row Operations (ERO)

Generally, Elementary Row Operations (ERO) can be defined as a multiplication and addition force that is imposed on the matrix rows. The three operations corresponding to the operations in rows of EROs are multiplied in the following way: a row by a non-zero constant; interchanging two rows; and then adding a multiple of one row to another row [44].

The purpose of these operations is to acquire a solution in algebra or to obtain a new form of matrix. For example, an arbitrary system of  $m$  linear equations in  $n$  unknowns can be written as:

$$\begin{aligned}
a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n &= b_1 \\
a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n &= b_2 \\
&\vdots \\
a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n &= b_m
\end{aligned} \tag{2.1}$$

where  $x_1, x_2, x_3, \dots, x_n$  are the unknowns and the subscripted  $a$ 's and  $b$ 's denote constants.

The above equation can be simplified by writing down only the constant values in the form of a rectangular matrix as follows:

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix} \tag{2.2}$$

By using the three operations above, the unknown variables can be derived.

### 2.5.2. Kronecker Product (KP) Operation

The definition of the Kronecker product or tensor product can be noted as follows [45]. Suppose  $A \in \mathbb{R}^{m \times n}$ ,  $B \in \mathbb{R}^{p \times q}$ . Then the Kronecker product of  $A$  and  $B$  is defined as the matrix:

$$A \otimes B = \begin{bmatrix} a_{11}B & \cdots & a_{1n}B \\ \vdots & \ddots & \vdots \\ a_{m1}B & \cdots & a_{mn}B \end{bmatrix} \in \mathbb{R}^{mp \times nq}$$

Obviously, the same definition holds if  $A$  and  $B$  are complex-valued matrices.

There are two advantages that can be obtained using this operation. First of all, it is able to change the value of each element of the original matrix. Secondly, if  $B$  has any kind of matrix form, this means that a new larger matrix can be generated with different dimensions.

## 2.6. Summary

In this chapter, the discussion has centred on the reasons why security is more important for biometric-based authentication systems than for non-biometrics systems. The main reason is that a biometric is permanently associated with a user and cannot be revoked or cancelled if compromised. In this case, if a biometric identifier is stolen and misused, it is lost indefinitely and possibly for every application where that biometric is used. In order to avoid any potential security crisis, vulnerabilities in the biometric system must be identified and addressed systematically. Cancellable biometrics has been a challenging but essential approach to protecting the privacy of biometric data. Therefore, protecting biometric information is a major concern.

According to [30], there were eight places in the generic biometric system that is vulnerable to be compromised. For example, some attacks can be perpetrated at the sensor level and at the feature extractor level by presenting a fake biometric at the acquisition process or resubmitting a sensor stored digitized biometrics signals. Meanwhile, in overriding the feature extraction process, the feature extractor is attacked using a Trojan horse, so that it produces feature sets pre-selected by the intruder.

Other attacks are related to the biometric templates generated by the feature extractor module, which are stored in the database or matched against previously stored templates. The biometric templates are the targets of the attacks either at the database level or at the

interconnecting channel level. Finally, the matcher and the output to the device application can be attacked to override the system decision.

Cancellable biometrics is a concept where the biometric template is secured by incorporating protection and replacement features into the biometrics. Fundamentally, cancellable biometrics alter the biometric images or features before being matched. The variability in distortion parameters offers the scheme its cancellable nature. A superior cancellable biometrics formulation must fulfil four requirements: to be distinctive and reusable, with unidirectional transformation and performance.

Based on these requirements, cancellable biometrics allows the system to re-issue the biometrics for a user. The key idea of cancellable biometrics is to distort the biometric image/signal/features before matching. The distortion parameters can easily be changed, which provides the cancellable nature of the scheme.

The performance evaluation of biometric-based authentication systems is an important issue. The authentication session compares a live biometric sample provided by the user with the user's reference template generated by the system during the enrolment procedure. This biometric matching determines the degree of similarity between the live submitted biometric sample and the reference template.

# Chapter 3

## 3. Biometric Fingerprint

### 3.1. Introduction

In this research, fingerprint technology is utilized as an input for the cancellable algorithm. This is influenced by the fact that a biometric fingerprint has certain unique features, such as minutiae, pore, core-point, ridge and valley, and the fingerprint itself. These features and traits provide particular information related to the owner so that no single other person has identical information. This uniqueness encouraged us to select fingerprint technology to provide the input for the cancellable algorithm.

In the previous chapter, it was stated that a cancellable template could be established by utilizing several matrix operations that are inverse operations; for instance, the Kronecker product operation and the elementary row operation. These operations yield a disguised transformed template so as to recognize an impostor. Using these matrix operations requires a quality-enhanced image as an input to ensure that there is no missing feature information whilst the cancellable template is being generated.

For fingerprint technology, a qualifying image can be obtained by implementing a pre-processing step to provide an enhanced fingerprint input for the cancellable fingerprint algorithm. This stage can minimize the possibility of obtaining false-feature information caused by noise, scars, unclear ridges/valleys, and so on. Another fingerprint processing step needed is core-point identification as a reference point to select a certain region for the fingerprint input. Moreover, the core-point is also utilized as an important requirement in the

classification step. The classification of a fingerprint is also utilized to reduce the time taken during the authentication step, especially for the identification process. By classifying the type of fingerprint, for instance, whorl, arch, tented arch, right loop, or left loop, this provides a simple way to reduce the number of fingerprints which need to be compared.

Furthermore, the core-point is needed for several other purposes as follows. Firstly, it means that a correct decision can be made with regards to which class a fingerprint is related to. Actually, in class determination, the core-point is at the centre of the fingerprint ridge plot pattern. Secondly, the core-point can be used as the core of the region of interest (RoI) of a registered fingerprint. Normally for fingertips, the core is positioned in the centre. Therefore, if the selection of the RoI uses the core-point as a zero coordinate, this is very useful in recognising all of the fingerprint features. Furthermore, by using the core-point as a point reference for a fingerprint, it helps to locate the minutiae details precisely in their own data positions during the authentication step.

Minutiae extraction is used as one of the inputs for the cancellable system. After minutia extraction, data on minutiae position will be dispersed in a row/column projection to specify the certain location of the minutia. The method used in spreading the minutia information is by collecting all minutiae caught in the extraction process afterwards and placing it all in a data table. Subsequently, for authentication purposes, it will be difficult to achieve a faster and efficient process, as a step-by-step initialization process is needed to check an enquiry minutia against a registered one. Otherwise, if the core point is used as a reference point, then the time taken can be reduced because the position of the minutia can be directly confirmed with the original one without firstly identifying the position of each minutia.

In this research, the possibility of establishing a cancellable fingerprint by using an enhanced fingerprint image such as with minutiae extraction is determined as well. The reason for this is that the minutiae observed by the naked eye do not show up as a fingerprint any more, and only appear as scattered figured points. However, implementing an improved minutiae extraction approach is required to omit false-recorded information for fingerprint recognition.

As previously mentioned, the RoI is required to ensure that all feature extraction such as minutiae are entirely covered. Furthermore, the RoI is also required to make certain that the input from the fingerprint will be in square form. Naturally, the fingerprint obtained from an acquisition process is a non-square fingerprint image. Meanwhile, a mathematical operation in matrices operations mostly requires a square form of matrix. Therefore, the cropping and selection of the region is necessary, even though a non-square output is produced later to obtain a dependable cancellable template.

Similarly to all issues of authentication of biometric output, a cancellable proposed algorithm will be worthless if it cannot recognize which enquiry fingerprint is valid and which one is an impostor. This means that it cannot be claimed that the cancellable fingerprint reliable without knowing how good it is in successfully passing the authentication process. Recently in the field of fingerprint research, minutia extraction has been acknowledged to be one of the most appropriate methods for authenticating an enquiry fingerprint. If more minutiae being accepted, as confirmed minutia, in the authentication process, This means that the authentication failure rate will be lower [19]. This justification is based on the fact that minutiae are an extraction of the unique links and furrows of the fingerprint, known as termination and bifurcation, means that each distinct fingerprint has its own unique minutiae pattern.

## 3.2. Fingerprint Enhancement

Given that the quality of fingerprint input is important, researchers have been encouraged to propose various approaches to fingerprint enhancement. For example, a Laplacian-like image pyramid has been used to spoil the form of the original fingerprint and to turn it into interconnected pieces with different special scales [46]. On an image level, where the filtering direction comes from symmetrical linear features, a contextual smoothing process has to be conducted.

One of the enhancement fingerprint algorithms that has been accepted as a key reference is based on the principle of image convolution using Gabor filters to apply local ridge orientation and ridge frequency [47]. The main steps of this algorithm cover the normalization of the ridge orientation calculation, ridge frequency calculation and filtering.

In order to facilitate various fingerprint applications, such as matching fingerprint [48], [49], and fingerprint classification [50], the fingerprint enhancement approach based on the Gabor filter can be taken into consideration. The Gabor filter is a type of band-pass filter that has two characteristics: being frequency-selective and orientation-selective [51]. The average values of those filters can effectively impose specific frequency and orientation values. The fingerprint is known to have characteristics of local ridge orientation and ridge frequency, and the enhancement algorithm benefits from the regulation of its spatial structure by applying Gabor filters to match local ridge orientation and frequency. Therefore, in this research, the Gabor filter is used so that ridge frequency and ridge orientation are utilized in various fingerprint processing step.

An alternative method to improve the quality of fingerprint features has been proposed which is known as the Fourier directional filtering technique [52]. In this research, the image enhancement process starts by computerizing the orientation image. This is different to previous techniques, which work in the spatial domain and involve spatial convolution toward an image through filters, as well as estimating ridge orientation using continuous estimation from its direction. However, this new proposed method operates in the frequency domain and allows the system to use only 16 groups of directions in calculating the orientation [52].

The approach to local estimation is called gradient-based, and has been studied by various researchers [53], [54], [55], and [56]. The dominant orientation is computerized using the gradient in the surrounding neighbourhood environment since gradient operators such as Premitt and Sobel [57] are sensitive to noise and pores (a fingerprint feature within the ridge).

Many techniques have been introduced from the field of orientation, in order to overcome the noise issue in the fingerprint. One that is commonly used is the smoothing process, based on the low-pass filter method [54]. Although this method is simple and effective, the size of the filtering window is the most critical parameter. A larger window will eliminate the noise better, while a smaller window will protect the correct orientation in the high curvature area. Several publications recommend using the multi-resolution of orientation areas in order to overcome this issue [58], [59], [60], and [61]. Unfortunately, the smoothing process cannot fix the correct orientation area if the noise is worse or hidden.

Various studies have implemented the smoothing process of the orientation area by using a Markov Random Field (MRF) or an energy minimization approach [62], [63], [64]. The limitation with this algorithm is that the orientation variable is connected to a small area of the image and can be represented by a single dominant orientation. However, the MRF

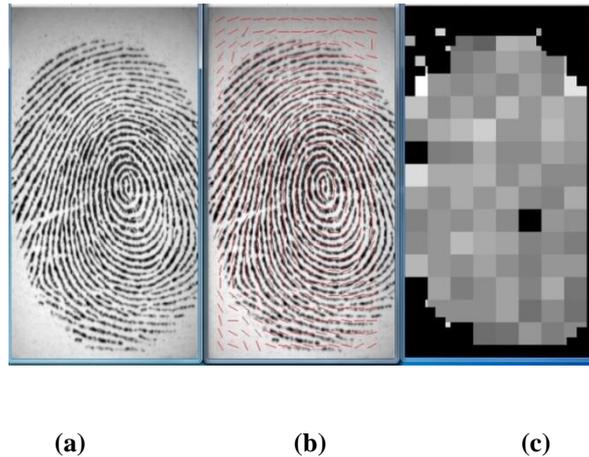
model with a small neighbourhood or small connection can only utilize the structure of a fingerprint that contains the main information [65], [66]. In addition, poor quality fingerprints cannot be used in this method.

Furthermore, several mathematical models have been proposed by a number of researchers with the purpose of describing all of the orientation area of the fingerprint. In addition, several models are commonly used, such as the polynomial [67], and Fourier series [68]. The models that are explicit consider single points and rely on their extraction. Nevertheless, the extraction of hidden single points contributes to the problems that might occur during the process. Due to this, the orientation field estimation approach [69], [70], [71], [72] is used as an input to specify the single points that are manually marked.

### 3.3. Core-Point Identification

The core-point application has obviously been used in the process of fingerprint classification and matching, no matter how precise or inaccurate its placement is. The core-point is also needed to calculate the number of ridge lines between the core and other reference points, such as the delta point. The direction of curvature (DC) technique is used to detect the raw core-point, while the geometry of region (GR) technique has been used to find the correct core-point by introducing the region of interest, in order to increase the accuracy of the core fingerprint [73]. Based on the similarity of ideas related to fingerprint classification, it has been argued that this approach should be based on how enhanced and reliable the image is of the orientation of the fingerprint [74].

Another approach proposed for finding the core-point detects the curvature in the fingerprint through the filtering complex method [75]. Here, the complex filter will be applied to the field ridge orientation from the result image of the original fingerprint.



**Figure 3.1. Core point detection using ridge frequency and ridge orientation steps of a fingerprint (a)Original fingerprint; (b)Ridge frequency step; (c)Ridge orientation step**

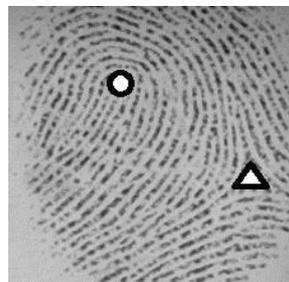
In this thesis, ridge frequency and ridge orientation processes are utilized to identify the core of the fingerprint. The pattern created from these two steps helps the developed algorithm to recognize and analyse the central of the fingerprint by optimizing the intersection of each patterns. The intersections trace a spotted area that is identified as an estimation of the core point. Decision to choose a point as a core is based on peak-sharp pattern form on the spotted area.

### 3.4. Region of Interest

In order to determine the desired working area and to more focus on the process of the analysis of part of the selected image, the selection of a certain area of an image, which is

also known as the region of interest (RoI), is also required. This stage of image processing can combine, extract, remove and transform the area resulting from the selection process into an image window. In biometrics, this selection process is needed to select numerous biometric characteristics that are accurate and contain less noise objects. For example, a fingerprint is normally obtained as a result of scanning process. This means that the fingerprint not only contains the information but is also surrounded by noise that becomes the background of the fingerprint.

Therefore, this selection procedure requires a determination that is used as a reference in choosing the desired proper area. As an example, in several cases of fingerprint, full fingerprint recognition is not needed as it only requires information about the delta and core-point sighting of that fingerprint. This is shown in Figure 3.2.



**Figure 3.2. Fingerprint and its Core-point (circle) and Delta (triangle)**

The RoI is obviously required as well when the field work domain is in matrix form. As is generally known, working in the matrices field usually requires a square-form image. Meanwhile, a fingerprint recognition input is mostly available in non-square form. Thus, implementing the RoI is an important step.

One author has proposed a new image-based fingerprint matching method for various rotations and translations of fingerprint input [76]. This approach combines the directions of ridges as a prominent feature component and describes the fingerprint in terms of the directional energies. The area of a particular radius that is detected around the reference point is used as the ROI for feature extraction.

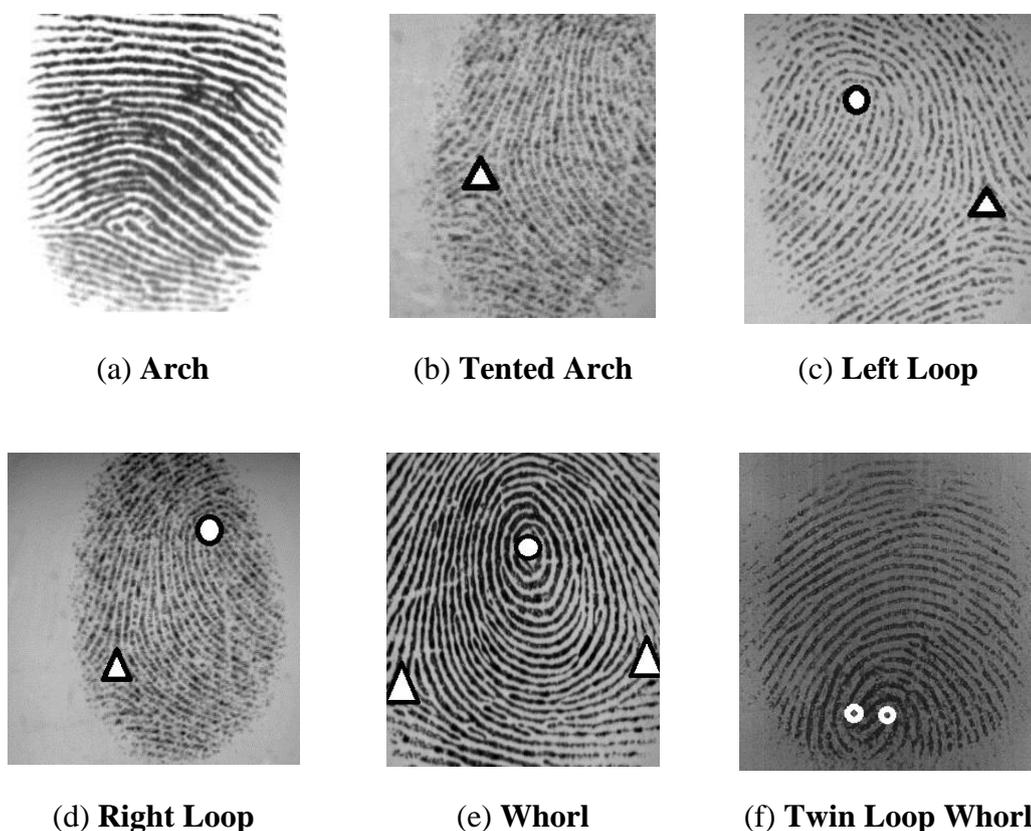
Another proposed application of the ROI is as an accurate object detector [77]. In this paper, the author discussed the approach used to determine the location of an object through selecting and classifying areas from the main object. The determination of the targeted area based on its similarity and also its spatial neighbourhood citations is also discussed.



**Figure 3.3. Region of interest step**

### 3.5. Fingerprint Classification

The first scientific study to thoroughly discuss finger classification was conducted by Sir Francis Galton in 1880 [78]. The classification process was introduced as the average of fingerprint indexing to speed up the process of locating a fingerprint in the database. In the last 10 years, Edward Henry has renewed Galton's work by introducing the concept of the core-point and delta of the fingerprint to meet the needs of fingerprint classification [79].



**Figure 3.4. Examples of the five commonly used fingerprint classes under the Galton-Henry classification scheme**

Even though the Galton-Henry scheme offers several benefits, such as being interpretable by humans and entailing the rigid segmentation of a database, only a small

number of classes can be automatically applied to the system. As an example, most of the automatic systems [80], [50], [81], [82], [83] can only classify fingerprints into six classes as shown in Figure 3.4.

Conversely, there are many fingerprints that cannot be easily distributed into classes and which cannot even be classified properly by an expert because of the ambiguity of the fingerprint features. Therefore, the Galton-Henry scheme that separates a fingerprint database into interpretable classes for humans will not be free from error. Moreover, this scheme does not offer fingerprint selectivity for a larger database. In fact, it is unnecessary for the automatic system to sort the database into fingerprint classes that can be interpreted by humans.

In the Automatic Fingerprint Identification System (AFIS), the purpose of the classification process is to reduce the area that needs to be searched. This purpose can be achieved by sorting the database into fingerprint machine-generated classes in the feature area, as long as the search is consistent and reliable. For example, some indexing fingerprint techniques [84], [85] can clear up the search area more efficiently than the scheme used by Galton-Henry.

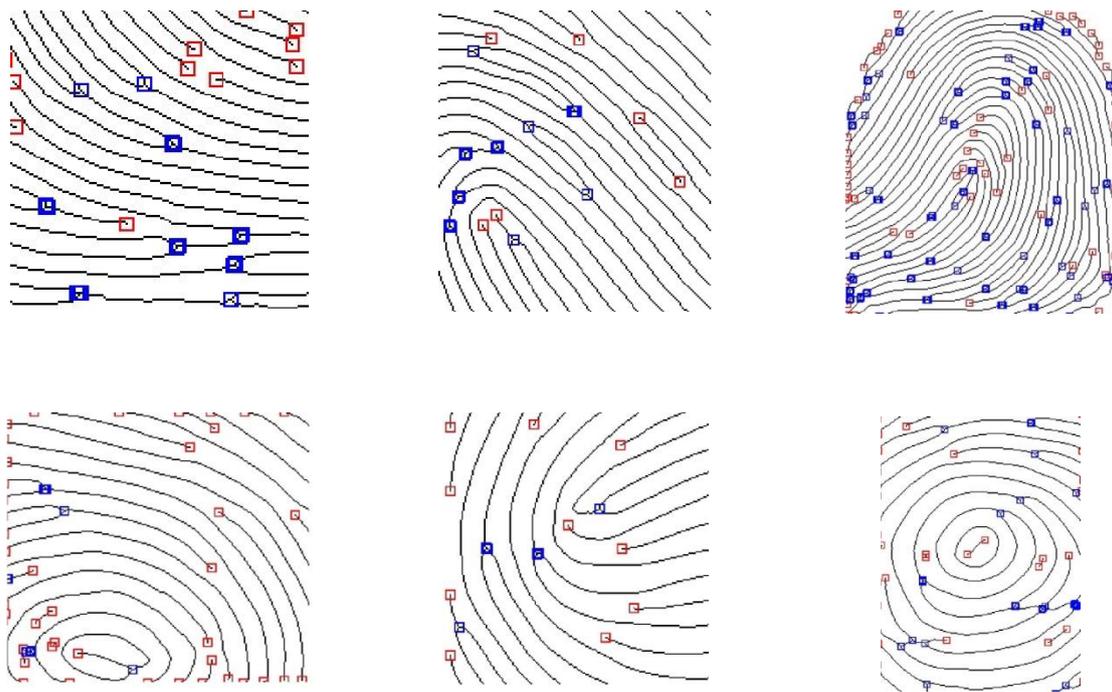
The classification techniques that are regularly being proposed [19], [86], [87] do not classify the database in the beginning, but represent each fingerprint with a numerical feature vector. Moreover, it gives a query fingerprint where a class is formed by regaining part of the fingerprint that has feature vectors in the database, in which the database has the proximity value with the query fingerprint. Although these techniques can classify fingerprints into a number of fingerprint classes, a query fingerprint is still required to be compared with all the fingerprints in the database, which can be time consuming for larger databases. This issue can

be prevented by using a technique combining groups of data in the fingerprint retrieval framework [87], [88].

### 3.6. Minutiae Extraction

Minutiae can be either of the termination or bifurcation types. A minutia is considered to be the bifurcation type if the end-point of the fingerprint ridge/valley has one input and two outputs, or vice versa. Meanwhile, it is considered to be the termination type if the ridge/valley has stopped at one end-point. Before the minutiae extraction stage, the fingerprint enhancement process is conducted if the fingerprint is assumed to include noise. This usually depends on the result of the quality extracted measurement, which is performed automatically [89], [90], [91], [92].

Most of the recent minutiae-based automatic fingerprint matching systems referred to by Jain et al. [7], and Maio and Maltoni [93] were proposed at the end of the 1990s. Jain et al. recommend a fascinating idea in matching performance, as long as the image quality of the fingerprint input is good. Meanwhile, compared with Jain et al., Maio and Maltoni offer a complete and robust approach so that the system can be more adapted to noise.



**Figure 3.5. Examples of the minutiae extraction of two different fingerprint database sources (FVC 2002 and BRC)**

### 3.7. Summary

In this chapter, the first subject discussed concerned the production of a dependable cancellable fingerprint that requires a fingerprint input with improved quality, so as to ensure that no feature information is missing from the fingerprint. That is why for most fingerprint image processes, including generating a cancellable fingerprint using matrices operations, two stages important in order to ensure success are image enhancement, such as by normalization, binarization, or quality mark-up and feature extraction such as by minutiae extraction, core-point identification, or pore extraction.

However, the performance of a fingerprint feature extraction and matching algorithm heavily depends upon the quality of the input of the fingerprint image. In reality, fingerprint

images are rarely of perfect quality. Given that the quality of a fingerprint image is not able to be measured objectively, it roughly corresponds to the clarity of the ridge structure in the fingerprint image. It can be judged as a qualifying image when it has well-defined ridges and valleys, and is of high contrast. Images may be degraded and corrupted with an element of noise due to many factors, including variations in skin and impression conditions.

Because a biometric property is an intrinsic trait of an individual, it is difficult to confidentially duplicate and virtually impossible to share. Moreover, the biometric properties of an individual can only be lost in the case of a serious accident. Even though automated biometrics can help alleviate the problems associated with the existing methods of user authentication, an assailant might still be able to locate several weak points in the system, making it vulnerable to attack. The problems with biometric authentication systems occurs when the data associated with a biometric feature has been compromised.

In the next chapter, a novel methodology to generate a cancellable biometric is discussed in detail. The relevant methodology is introduced in term of generating a cancellable fingerprint feature.

# Chapter 4

## 4. Matrix Operations and Cancellable Fingerprint

### 4.1. Introduction

The main aim in generating cancellable biometrics is the production of a reliable revocable biometric template. A cancellable biometric is needed to protect an authorized persons information from an impostor. One way of doing this is by randomizing the original biometric feature to generate a vague image. In this thesis, the disguising process is achieved using three matrices operations: the elementary row operations (ERO), the Kronecker product (KP) operation and an inverse matrix operation.

This idea is to deliver one of the cancellable biometric approaches, because using ERO, KP, and inverse operations can allow several alternatives in randomizing the original image as long as it is able to satisfy the three requirements of non-invertible matrices:

1. At least one row or column of the original matrix should be of zero (0) value.
2. The original matrix must be modified into a non-square matrix form.
3. It must be ensured that none of the rows is a multiple of another row.

Meanwhile, the Kronecker/tensor product is used to provide a large, non-invertible and totally different cancellable biometric image when compared with the original biometric image.

## 4.2. Basic Idea of Generating Cancellable Features

A feature can be categorized as cancellable when it is non-invertible to the original image. The same thing applies to matrices. The matrix cannot be inverted when satisfying three situations:

1. There is one zero row at least.
2. There is a row that is a multiple of another row.
3. The matrix form is not a square.

The first requirement can be achieved using the elementary row operation (ERO), where a selected row is multiplied by zero. Meanwhile, for the next requirement, given that it is rare to find a row in an image system which is a multiple of another row, this can be created by using ERO. Furthermore, to ensure that the obtained cancellable matrix is completely masked and to be able to meet the last requirement for the non-invertible matrix, in this research each element of the transformed matrix is multiplied by an arbitrary matrix/element. This process is called the Kronecker product or tensor product operation. By using this process, the outcome is that both matrices have numerous elements and an adjustable matrix form (whether a rectangular or square matrix).

As matrices are used in this field, then there should be no noise at all because the existence of noise may add specific information to the biometric feature. The noise on the fingerprint can be occurred when the surface of the scanner in the acquisition process is unclear. This is relevant for a cancellable biometric, since the final stage of this system is the authentication process and even a small amount of noise will significantly affect the quality of the cancellable feature and will certainly result in low precision during the verification

process later on. Thus, the early process to be undertaken towards the result of the established fingerprint is an enhancement step. The enhanced fingerprint will provide a feature with the precise value of fingerprint information so that when it is extracted to domain matrices, no unnecessary values will go into it. After following several fingerprint steps, the cancellable input image will be produced by several matrices operations.

In view of the fact that it is already in a matrix domain, then the next issue to be discussed is how to build the cancellable biometrics system using an input matrix  $A$ . Firstly, matrix  $A$  will be inverted as the first step in disguising the real feature. This idea is an initial step, as it will be considered whether directly inverting matrix  $A$  is effective or, conversely, inverting matrix  $A$  after another matrix operation. The next step will be to determine whether to apply the elementary row operation (ERO) to matrix  $A$  to obtain a zero-value row or to apply the Kronecker Product (KP) operation. It is also necessary to determine how many zero rows are required to achieve the required maximum non-invertible matrix. Besides the use of ERO to obtain zero rows, another method to be considered in this research is the use of ERO to create rows that are the multiples of other rows.

After implementing the ERO operation with matrix  $A$ , the result of this operation can be named matrix  $K$ . This will then go through a KP operation to produce a KP matrix, where every initial element is unrecognizable. Let us name this matrix  $M$ . In this KP operation, matrix  $K$  will be multiplied by a tensor factor that can be in the form of a matrix or integer with a constant value called  $B$ . The form and value of factor  $B$  will be further investigated in this research. For example, if factor  $B$  is a matrix, then the value can be taken from the numbers given by a person who has registered his biometrics when registering as an authentic person for a biometric whose cancellable feature is being created. In this research, the steps using ERO and KP will be analysed as well, including whether the use of ERO in the beginning and KP afterwards is better, or vice versa. The result of this process will be a

cancellable matrix of matrix A, which will be seen specifically as matrix C which is a cancellable template.

### 4.3. Matrix Implementation

The above processes can be illustrated using the following mathematical steps. It can be noted that the original input matrix A is a three-by-three matrix. The first alternative step that is used is to invert the original matrix, so as to disguise it.

$$A^{-1} = \frac{1}{|A|} \text{adj}A \quad (4.1)$$

$$\text{Supposing } A = \begin{bmatrix} 2 & 5 & 7 \\ 3 & 2 & 0 \\ 8 & 9 & 6 \end{bmatrix}, \quad (4.2)$$

where  $|A|=11$ , and

$$\text{adj}A = \begin{bmatrix} 12 & 33 & 11 \\ -18 & -44 & 21 \\ 11 & 22 & -11 \end{bmatrix}, \quad (4.3)$$

so that,

$$A^{-1} = \begin{bmatrix} \frac{12}{11} & 3 & -\frac{14}{11} \\ -\frac{18}{11} & -4 & \frac{21}{11} \\ 1 & 2 & -1 \end{bmatrix}, \quad (4.4)$$

To obtain the Kronecker product ( $KP$ ), another matrix should be determined. In order to provide more of an overview, there are two alternatives for that matrix; firstly, a non-square form matrix  $B$  observed as in the matrix below

$$B = \begin{bmatrix} 11 & 11 \\ 0 & 0 \\ 11 & 11 \end{bmatrix}. \quad (4.5)$$

The reasons for establishing this matrix are firstly to show why a non-square matrix cannot be inverted; and secondly, why if there is at least one zero row, the matrix cannot be

inverted as well. Furthermore,  $A^{-1} \otimes B = \begin{bmatrix} \frac{12}{11} & 3 & -\frac{14}{11} \\ -\frac{18}{11} & -4 & \frac{21}{11} \\ 1 & 2 & -1 \end{bmatrix} \otimes \begin{bmatrix} 11 & 11 \\ 0 & 0 \\ 11 & 11 \end{bmatrix} =$

$$KP = \begin{bmatrix} 12 & 12 & 33 & 33 & -14 & -14 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 12 & 12 & 33 & 33 & -14 & -14 \\ -18 & -18 & -44 & -44 & 21 & 21 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ -18 & -18 & -44 & -44 & 21 & 21 \\ 11 & 11 & 22 & 22 & -11 & -11 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 11 & 11 & 22 & 22 & -11 & -11 \end{bmatrix}; \quad (4.6)$$

where  $KP$  matrix is a 9 x 6 form (non-square matrix).

A matrix can be said to have an inverse if  $A.A^{-1} = I$ ; where  $I$  is a matrix identity. Meanwhile, a matrix is able to be a matrix identity if the diagonal elements of the matrix are 1 (one), whereas the other elements are 0 (zero). Based on this requirement, the matrix

identity should be a square form matrix. Since 9 by 6 is not a square form matrix, this proves that the  $KP$  matrix does not have an inverse.

The next alternative is a non-square form matrix  $B$  observed as the matrix below:

$$B = \begin{bmatrix} 11 & 11 & 11 \\ 0 & 0 & 0 \\ 11 & 11 & 11 \end{bmatrix}. \quad (4.7)$$

$$\text{That, } A^{-1} \otimes B = KP = \begin{bmatrix} \frac{12}{11} & 3 & -\frac{14}{11} \\ -\frac{18}{11} & -4 & \frac{21}{11} \\ 1 & 2 & -1 \end{bmatrix} \otimes \begin{bmatrix} 11 & 11 & 11 \\ 0 & 0 & 0 \\ 11 & 11 & 11 \end{bmatrix}$$

$$KP = \begin{bmatrix} 12 & 12 & 12 & 33 & 33 & 33 & -14 & -14 & -14 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 12 & 12 & 12 & 33 & 33 & 33 & -14 & -14 & -14 \\ -18 & -18 & -18 & -44 & -44 & -44 & 21 & 21 & 21 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -18 & -18 & -18 & -44 & -44 & -44 & 21 & 21 & 21 \\ 11 & 11 & 11 & 22 & 22 & 22 & -11 & -11 & -11 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 11 & 11 & 11 & 22 & 22 & 22 & -11 & -11 & -11 \end{bmatrix} \quad (4.8)$$

Currently, the form of the matrix  $KP$  is square (9 by 9). This 9 by 9 matrix can be inverted when  $KP.KP^{-1} = I$ . In this case, the matrix identity can be symbolized as matrix  $C$  and the  $KP^{-1}$  as matrix  $P$ : where,

$$C = \begin{bmatrix} C_{11} & C_{12} & C_{13} & C_{14} & C_{15} & C_{16} & C_{17} & C_{18} & C_{19} \\ C_{21} & C_{22} & C_{23} & C_{24} & C_{25} & C_{26} & C_{27} & C_{28} & C_{29} \\ C_{31} & C_{32} & C_{33} & C_{34} & C_{35} & C_{36} & C_{37} & C_{38} & C_{39} \\ C_{41} & C_{42} & C_{43} & C_{44} & C_{45} & C_{46} & C_{47} & C_{48} & C_{49} \\ C_{51} & C_{52} & C_{53} & C_{54} & C_{55} & C_{56} & C_{57} & C_{58} & C_{59} \\ C_{61} & C_{62} & C_{63} & C_{64} & C_{65} & C_{66} & C_{67} & C_{68} & C_{69} \\ C_{71} & C_{72} & C_{73} & C_{74} & C_{75} & C_{76} & C_{77} & C_{78} & C_{79} \\ C_{81} & C_{82} & C_{83} & C_{84} & C_{85} & C_{86} & C_{87} & C_{88} & C_{89} \\ C_{91} & C_{92} & C_{93} & C_{94} & C_{95} & C_{96} & C_{97} & C_{98} & C_{99} \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}; \quad (4.9)$$

From the matrix above, it is clear that the diagonal elements of  $C$  should be 1 and the others 0.

The computation can be simplified by firstly checking the diagonal elements of  $KP \times KP^{-1}$  or  $KP \times P$  ( $C_{11}, C_{22}, C_{33}, C_{44}, C_{55}, C_{66}, C_{77}, C_{88}, C_{99}$ ); where,

$$\begin{aligned} C_{11} = & (12 \times P_{11}) + (12 \times P_{21}) + (12 \times P_{31}) + (33 \times P_{41}) + (33 \times P_{51}) + (33 \times P_{61}) + (-14 \times P_{71}) + \\ & (-14 \times P_{81}) + \\ & (-14 \times P_{91}) \end{aligned} \quad (4.10)$$

$$\begin{aligned} C_{22} = & (0 \times P_{12}) + (0 \times P_{22}) + (0 \times P_{32}) + (0 \times P_{42}) + (0 \times P_{52}) + (0 \times P_{62}) + (0 \times P_{72}) + (0 \times P_{82}) + \\ & (0 \times P_{92}) \end{aligned}$$

$$= 0 \implies \text{this means that } C \neq I \text{ (matrix } C \text{ is not equal to matrix identity); (4.11)}$$

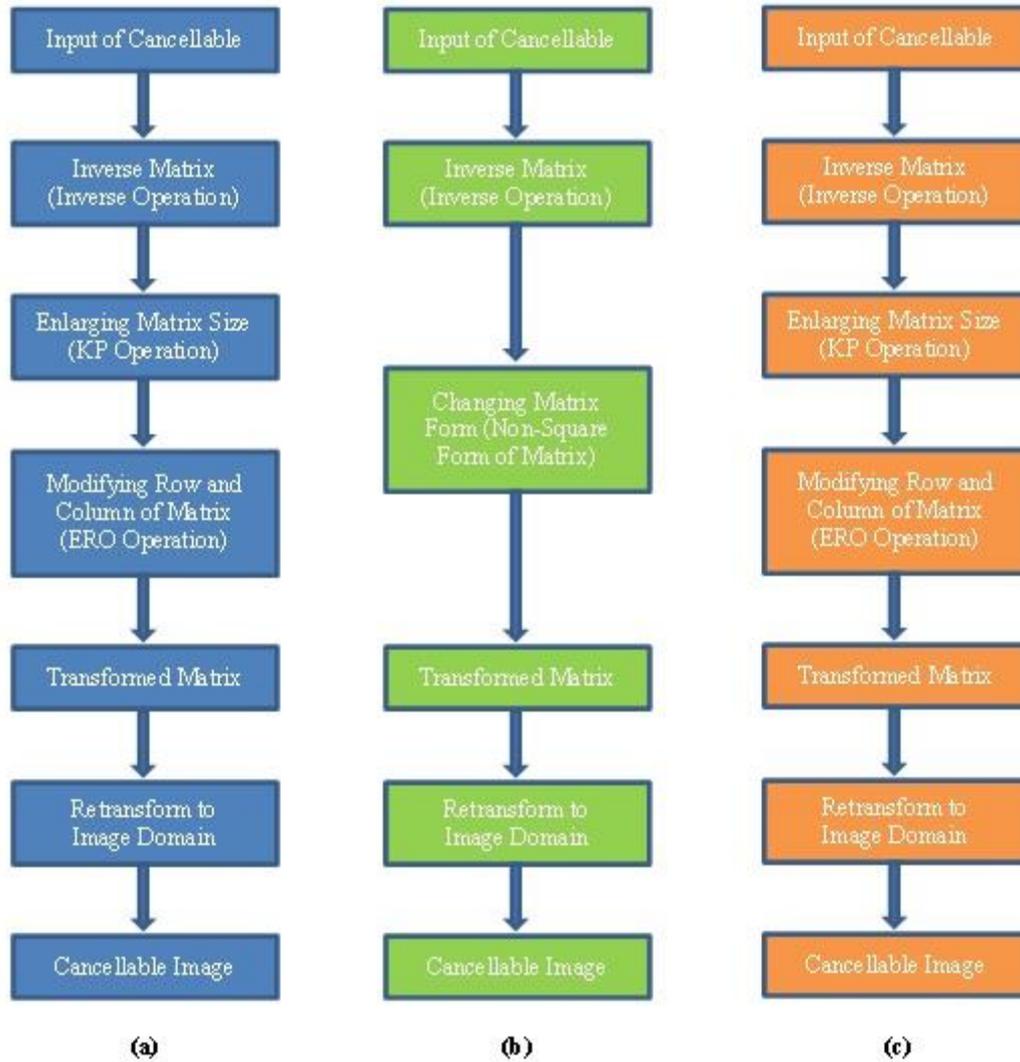
In summary, it can be said that matrix  $KP$  is a non-invertible matrix.

Referring to the explanation in the two previous sub sections above, it is obvious that matrix operations such as the elementary row operation (ERO) and Kronecker product operation (KR) can be implemented to generate a cancellable biometric. This is based on a similar approach between a cancellable biometric and a non-inverted matrix. In the former field, a cancellable method can be said to be successful when the yield image is not able to be retransformed into the original image. The same goes for the latter field. In the matrix domain, if the goal is to obtain a revocable matrix, then the non-inverse matrix requirement should be fulfilled to make the matrix non-invertible.

#### 4.4. Algorithm Outline

A feature can be categorized as a cancellable feature when it is non-invertible to the In this novel research, the first step to be achieved is to prove that implementing several matrix operations to produce a revocable biometric image can be used as a novel approach in the cancellability field. Therefore, in this research step, pre-processing steps have thus far not been discussed.

Nevertheless, a good quality input image is obviously required, as the work will be undertaken in a matrix domain. Consequently, a recent method related to this issue is discussed in the next chapter of this thesis. Generally, the outline of this proposed research is as shown in Figure 4.1. whereas the input of cancellable is the result of all of the fingerprint pre-processing steps used in this research.

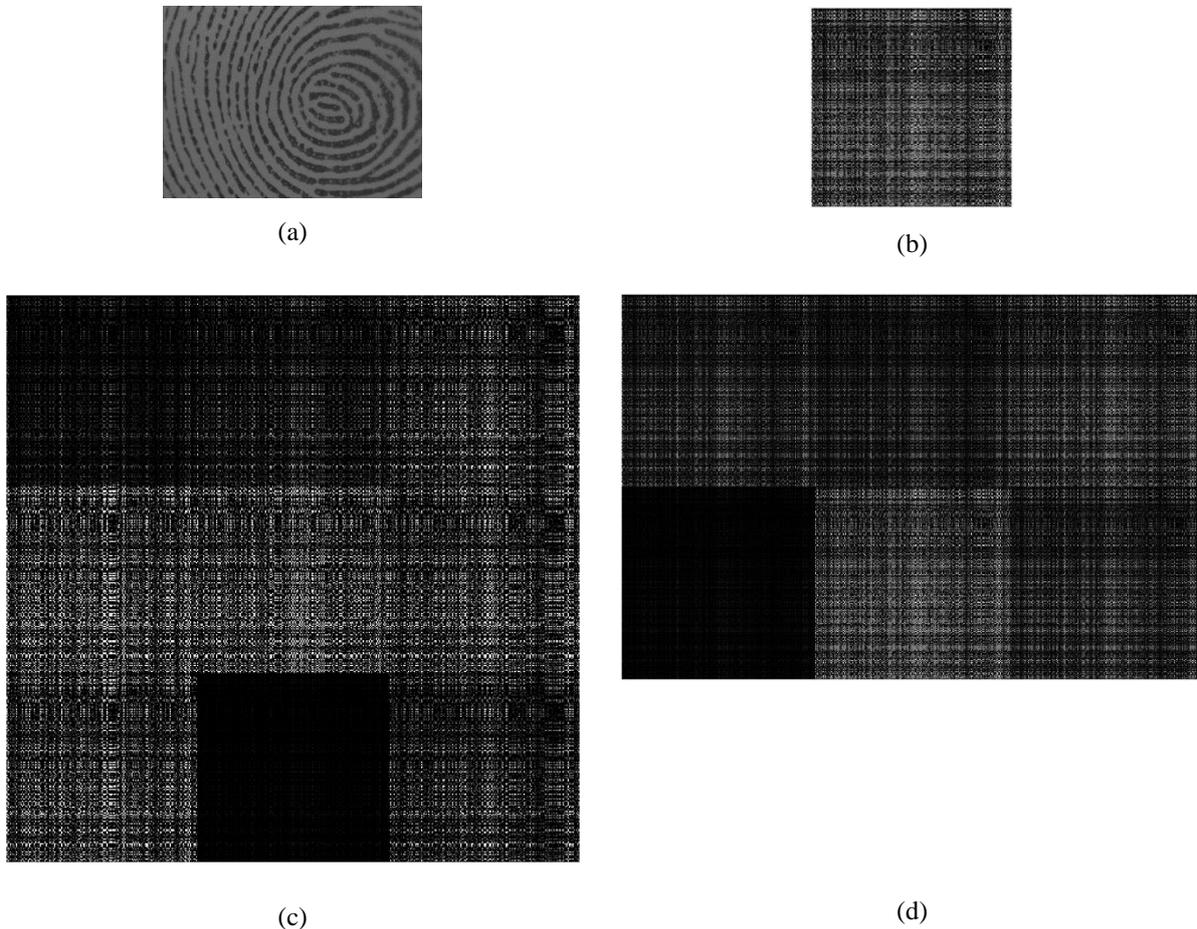


**Figure 4.1. Three approaches in generating a cancellable image using several matrix operations (a) the first alternative procedure; (b) the second alternative procedure; (c) the third alternative procedure**

## 4.5. Experimental Results and Discussions

In this work, the fingerprint has been chosen arbitrarily as the first biometric input. Three different benchmark fingerprint databases are used to verify to what extent the enhancement algorithm is appropriate for implementation. Those databases are: FVC 2002, DB1\_B to DB4\_B [94]; FVC 2004, DB1\_B to DB4\_B [95]; and BRC,

DBI/DBII/Training/Test [96]. In this case, images of BRC are utilized as follows, especially in generating a cancellable biometric:



**Figure 4.2. Implementation result of the first procedure of the research outline**  
**(a) Fingerprint original image 240 x 320 pixels; (b) Image as yield of inverse operation (240 x 240 pixels);**  
**(c) Kronecker Product operation's image with  $B$  as a multiplied matrix is a square matrix (720 x 720 pixels);**  
**(d) Kronecker Product operation's image with  $C$  as a multiplied matrix is a non-square matrix (480 x 720 pixels);**

To implement the matrix operations with a fingerprint, these operations have been implemented in accordance with three different procedures. As shown in the notes for Figure 4.2., a fingerprint with  $240 \times 320$  pixels is used as the input. As the algorithm is implemented in the matrix domain, a square form of input is needed to be processed in all of matrices

operations, and so the input feature is cropped independently into  $240 \times 240$  pixels of image. Using the BRC (Biometric Research Centre) database in this first experiment helps us to simplify the cropping process. Given that the foreground of the image is the fingerprint, the square form is obtained by selecting a point starting from 0 to 239 pixels from each side of the image.

In the first step, the cropping feature should be imposed as an inverse operation to camouflage the original feature of the fingerprint (Fig. 4.2(b)). Naturally, this step can be utilized to disguise the appearance of the original fingerprint because each pixel in the fingerprint is transformed into a different value. Thus, this means that it is already a new feature. This condition is helpful if the appearance of the feature is not similar to the appearance of a fingerprint feature so as to mislead and deceive an imposter.

Nevertheless, the feature imposed by the inverse operation is enough to restrict an imposter from knowing the original feature of the fingerprint or the appearance of the feature of the fingerprint. By re-inverting the inverted image, original feature can be reconstructed again. Consequently, another matrix operation, the KP operation, is conducted in order to improve the blurring of an inverted transform feature by expanding every pixel in the feature (Fig. 4.2(c) and (d)). The expanding processes are accomplished by magnifying the inverted feature with an arbitrary form of matrix/image. The arbitrary matrix/image could be  $m \times m$  (square form) or  $m \times n$  (not square form).

Nevertheless, to strengthen the blurring process, the ERO operation is applied to into the image of the KP operation by determining several rows/columns of the matrix to be transformed to zero by implementing the following approach.

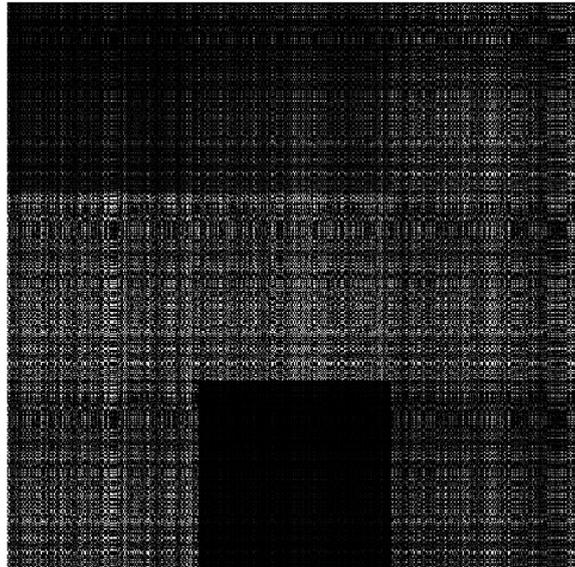
$$f(A) = mA + nC, \quad A = 1, \dots, m \text{ if } m < n \text{ and } A = 1, \dots, n \text{ if } m > n; C \in \mathbb{R}; \quad (4.12)$$

where :  $f(A)$  is the row which becomes zero,

$A$  is the selected row,

$m$  and  $n$  are a row and coloum.

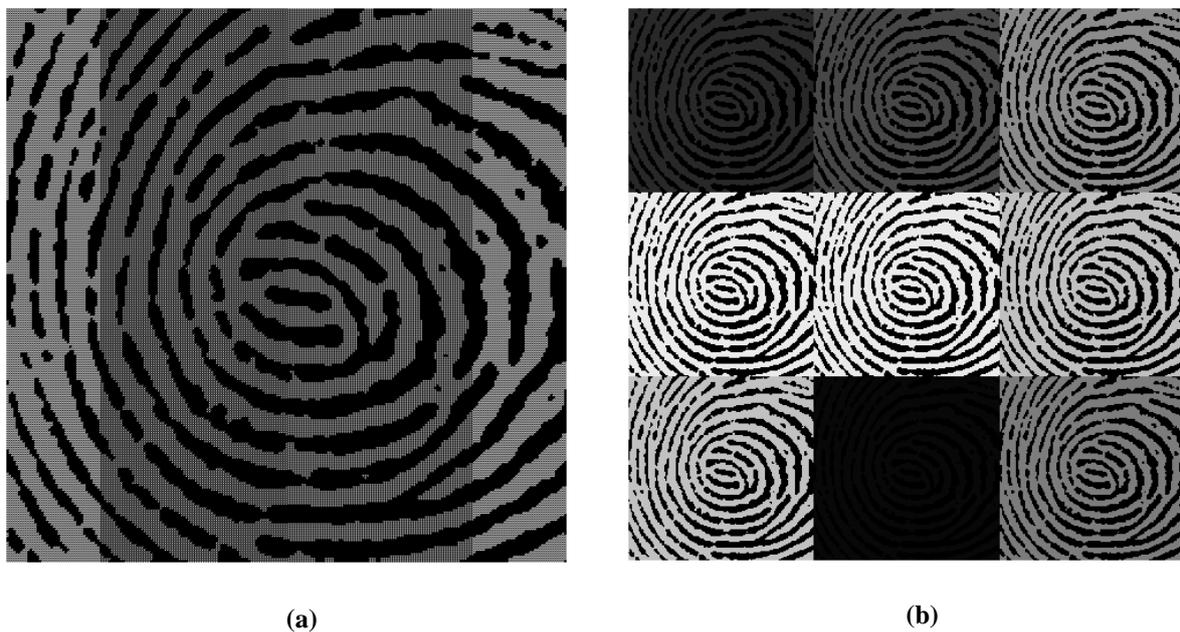
The above equation helps to determine which row the ERO is applied to and restrains this matrix operation due to the excessive number of zero rows. Basically, the ERO's yield feature is quite similar to the KP's feature, although it is different in value. This similarity helps to divert an imposter if they try to invert a cancellable feature to detect the original version of the fingerprint. In this step, the ERO yields a cancellable fingerprint feature (Figure 4.3).



**Figure 4.3. Image as a result of elementary row operation (the cancellable fingerprint image)**

Furthermore, the way to confirm the reliability of the cancellable feature is similar to the method used to ascertain the original matrix in the matrix domain. Thus, inverting the targeting matrix is known as the ultimate matrix. Based on this theory, the matrix of the image in Figure 4.3 is imposed using the inverted step. As a result, the cancellable matrix/image cannot be obtained again. This means that this cancellable biometric approach is successful.

Mathematically, a non-square arbitrary matrix in the KP operation can yield a cancellable feature as it cannot be inverted to determine the original. However, this result is still not eligible, given that someone can predict the value of the arbitrary matrix by extracting the value of each pixel in the KP's yield feature.



**Figure 4.4. Another approach to the procedure of the proposed research outline ( $720 \times 720$  pixels) by exchanging the placing combination of the Kronecker operation  
 (a)The Kronecker result of [input  $\otimes$  B matrix]; (b) The Kronecker result of [B matrix  $\otimes$  input]**

Subsequently, another approach with the outline algorithm is shown in Figure 4.4. In this alternative approach, a KP operation is applied to a cropped fingerprint input by first using a square form arbitrary matrix to manipulate the value of each pixel in the fingerprint. Two different procedures are implemented in this step. The first one, the input, which can be called matrix  $I$ , is magnified by matrix  $G$  ( $g \times g$ ), which is the arbitrary matrix. This process will cause a pixel from the input matrix to expand  $G$  times from the original one. Visually, this step gives an identical fingerprint image to the original, although in a large square form as shown in Figure 4.4 (a).

The subsequent process is obtained by calculating the arbitrary  $G$  matrix with an  $I$  matrix. It reduplicates matrix  $I$  into  $g$  number of the  $I$  matrix. In Figure 4.4(b), nine  $I$  matrices with different intensities are composed forming a large square form. Similarly to the previous procedure, the display of this KP operation product is still a copy of the original fingerprint. This means that a person is still able to recognize whom the fingerprint belongs to.

Meanwhile, for a non-square arbitrary matrix approach, termed as a  $K$  ( $m \times n$ ) matrix, the KP operation results are shown as follows.

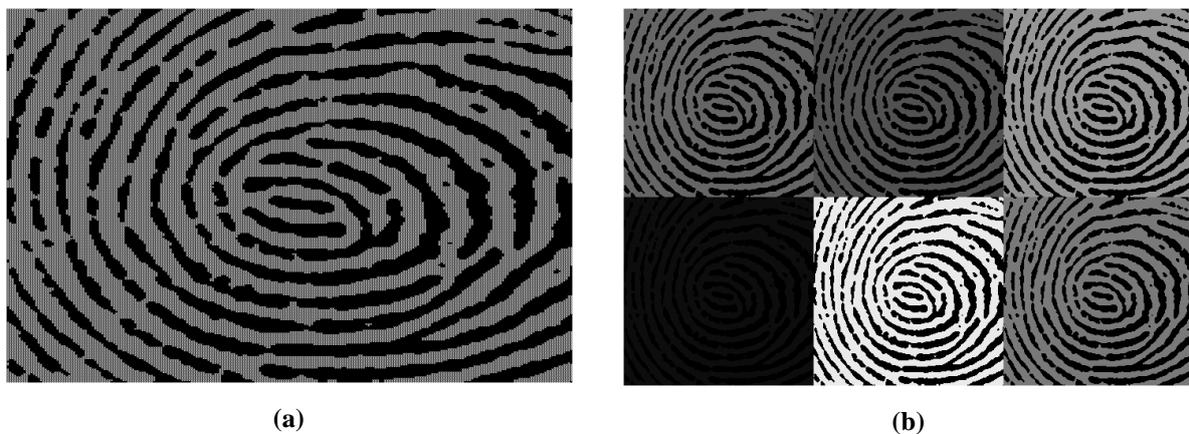
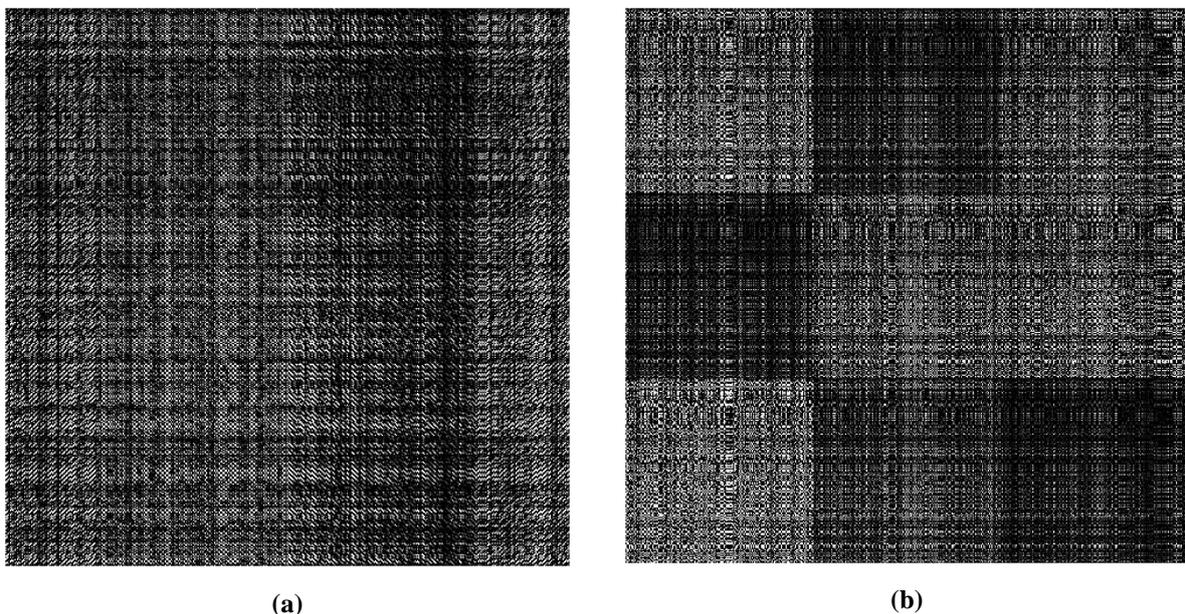


Figure 4.5. Result of the KP operation in the second alternative procedure of the research outline ( $480 \times 720$  pixels)

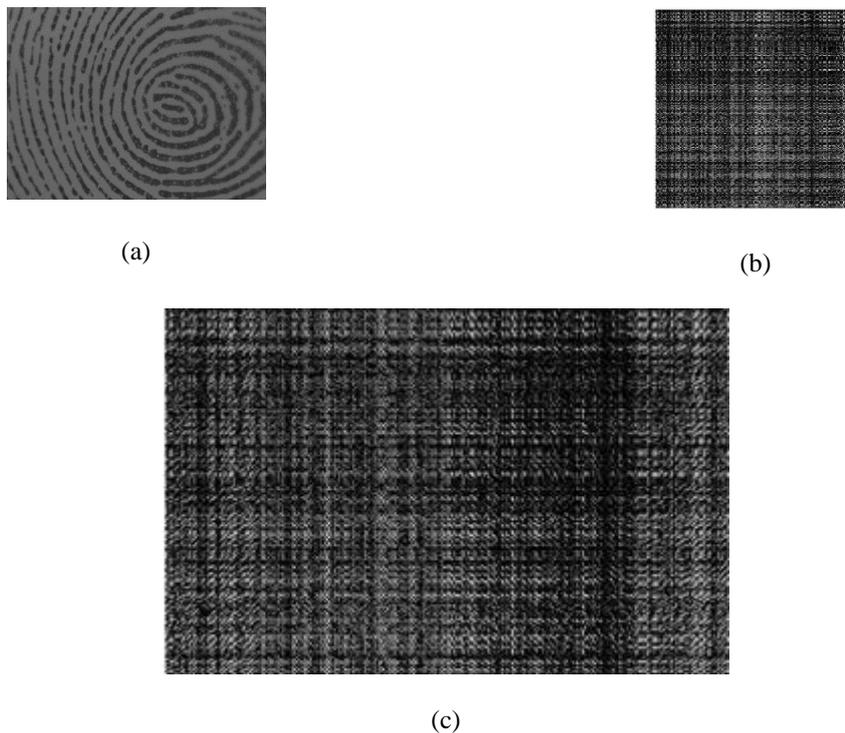
It can be noted that the result is not different in appearance, as the arbitrary matrix is in a square form. The KP figures expand as a large number of rectangular rows and columns of the  $K$  matrix. Meanwhile, details of the original fingerprint still exist in the pictures.

After imposing the KP operation, in the second method, the KP yield figure is inverted and the ERO operation applied. However, by using the same formula (4.52) with the first process in the ERO step, this procedure's aim is to change the position and number of several rows or columns of the fingerprint KP yield image. The values of several rows change to zero whilst a few rows have values different from the original. The result of this ERO process is known as a cancellable feature for the second procedure, shown in Figure 4.6(a) and (b).



**Figure 4.6. Images of the cancellable algorithm**

Based on the fact that, visually, the fingerprint is still able to be observed using the second approach, even though it produces a cancellable feature as well (see Figure 4.6.), it is recommended not to use this method. In an earlier discussion, one of the objectives of this research is to generate an unseen biometric image; thus, the first procedure is still recommended to be used as an algorithm.



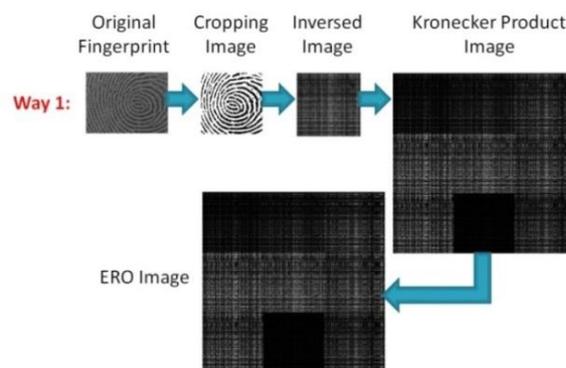
**Figure 4.7. the third procedure of the research outline  
(a)an image of the input of fingerprint; (b)an image of the cancellable template with a square form; (c)an image of the cancellable template with a non-square form**

The third procedure involved inverting the cropped image and then to continue by changing the matrix form of its result using the KP operation. This procedure aims to find a distinguishing feature as early as possible to camouflage the original fingerprint features. Figure 4.9 (c) shows a rectangular form of a fingerprint as a cancellable feature of a fingerprint after imposing the KP operation ( $m \times n$  arbitrary matrix). Actually, this process

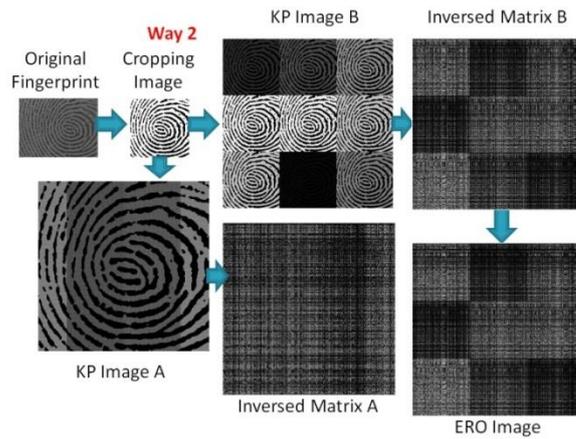
has a benefit in terms of time complexity since it undergoes no ERO step, wherein the latter step sometimes consumes 30 to 40% of all the required time to generate the cancellable fingerprint. However, this step has a disadvantage, especially if the arbitrary matrix in the process is identified by an imposter.

## 4.6. Summary

In this chapter, it is noted that the proposed approach can be relied upon to generate a cancellable template. It can be said that if the information data of the input of the fingerprint is not similar to the cancellable template, the proposed cancellable template is irrevocable. In fact, there are three procedures that can be used to produce it: firstly, by inverting-enlarging-rotating the image matrix as can be observed in Figure.4.8.

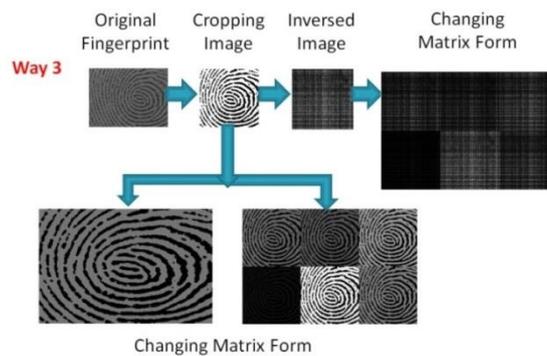


**Figure 4.8. Illustration flow of the first procedure of the research outline**



**Figure 4.9. Illustration flow of the second procedure of the research outline**

The second procedure is enlarging-inversing-rotating the image matrix (Figure 4.9.), and the last is by inversing-charging the matrix form (Figure 4.10.). Nevertheless, based on the results for all procedures, the first method is preferred for the algorithm so as to acquire the cancellable biometric template.



**Figure 4.10. Illustration flow of the third procedure of the research outline**

Furthermore, the pre-processing stage plays an important role, especially when the verification step is implemented as illustrated in Figure 4.11. It is shown that the matrix in

Fig.4.11(a), which is a matrix with an enhanced process, has a different information data compared to the matrix in Fig.4.11(b) which is using B pre-processing algorithm.

$$\begin{array}{ccc}
 \left| \begin{array}{cccccc} 1 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & \boxed{0} & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 1 \end{array} \right| & & \left| \begin{array}{cccccc} 1 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & \boxed{1} & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 1 \end{array} \right| \\
 \text{(a)} & & \text{(b)}
 \end{array}$$

**Figure 4.11. Illustration of the Importance of Pre-Processing Step for Fingerprint. Deviation value occurs (red square): (a) The pre-processing matrix of an A pre-processing algorithm; (b) The pre-processing matrix of an B pre-processing algorithm**

At the moment, there is an element of matrix in the original image, as a result of a pre processing step that does not have value as to what it is; therefore, the image will be rejected in the verification process. This is because in this procedure, each of the element values describe what the image is, no matter what.

# Chapter 5

## 5. Dependable Cancellable Fingerprint

### 5.1. Introduction

In this research, the steps in fingerprint processing are: fingerprint pre-processing, core-point identification, Region of Interest (RoI), fingerprint classification, minutiae extraction and fingerprint authentication. These are implemented to acquire a dependable cancellable fingerprint. The pre-processing step is required to provide a better quality fingerprint as an input for the cancellable fingerprint algorithm. This stage can minimize the possibility of obtaining false-feature information caused by noise, scars, or unclear ridges/valleys. The core-point is needed as a reference point to select a certain region for the fingerprint input. Moreover, the core-point is also utilized as an important requirement in the classification step.

Producing a cancellable fingerprint using matrices operations demands a square form image as an input. Given that most fingerprint recognition images are not square form, it is vital to implement the RoI step. Moreover, this stage is able to omit an ineffective part of the fingerprint image so that only a true feature is extracted during the feature extraction process.

Fingerprint classification aims to split fingerprints in a database into different types based on their pattern combinations. This step is required because by classifying a fingerprint as either a registered or verified one, the time consumption problem in the authentication process might be alleviate. Moreover, fingerprint classification can become more accurate in recognising the authenticity of a fingerprint.

Nevertheless, the possibility of establishing a cancellable fingerprint by using an enhanced fingerprint image such as by minutiae extraction needs to be determined as well. The reason for this is that minutiae are not visible to the naked eye and appear as a scattered set of points. However, implementing an improved minutiae extraction approach is required to omit false recorded information for fingerprint recognition.

Furthermore, the performance of a fingerprint feature extraction and matching algorithm depends heavily upon the quality of the input image. In reality, fingerprint images are rarely of good quality. As the quality of a fingerprint image cannot be measured objectively, it roughly corresponds to the clarity of the ridge structure in the fingerprint image. An image can be judged as qualifying image when it has well-defined ridges and valleys and high contrast. However, images may be degraded and corrupted with elements of noise due to many factors including variations in skin and impression conditions.

## 5.2. Fingerprint Enhancement

The aim of fingerprint image enhancement is to improve the quality of fingerprint input to make further operations easier. If it is presumed that the fingerprint images acquired from sensors or other media are not of sufficient quality to increase the contrast between the ridges and furrows and to connect falsely broken points of the ridges due to noise caused by the use of ink, enhancement methods are helpful in maintaining superior accuracy in fingerprint recognition.

In this research, although a novel fingerprint enhancement technique is not required, this general step is needed to compare the results from a cancellable fingerprint with and without an enhancement step. Nevertheless, several methods have been proposed for

enhancing the quality of fingerprint images. Firstly, the background and foreground regions of the fingerprint image should be separated using an image segmentation step. The next step is to standardize the intensity value in the image by adjusting the range of grey-level values into a desired range of values. This step is called image normalization.

Furthermore, ridge orientation and frequency are important to consider in fingerprint recognition as well. Ridge orientation is a fundamental step in the enhancement process, in order to effectively improve the quality of the fingerprint image. Moreover, the subsequent Gabor filtering stage relies on local orientation. In addition to the image orientation, the local ridge frequency step is another important process that is used in constructing the Gabor filter.

The last two steps are binarization and thinning processes. Binarization is the process that converts a grey level image into a binary image. This improves the contrast between the ridges and valleys in the fingerprint image, and consequently facilitates the extraction of minutiae. The final stage is the thinning process. This step is a morphological operation that successively erodes away the foreground pixels until they are one pixel wide.

### 5.3. Core-Point Identification

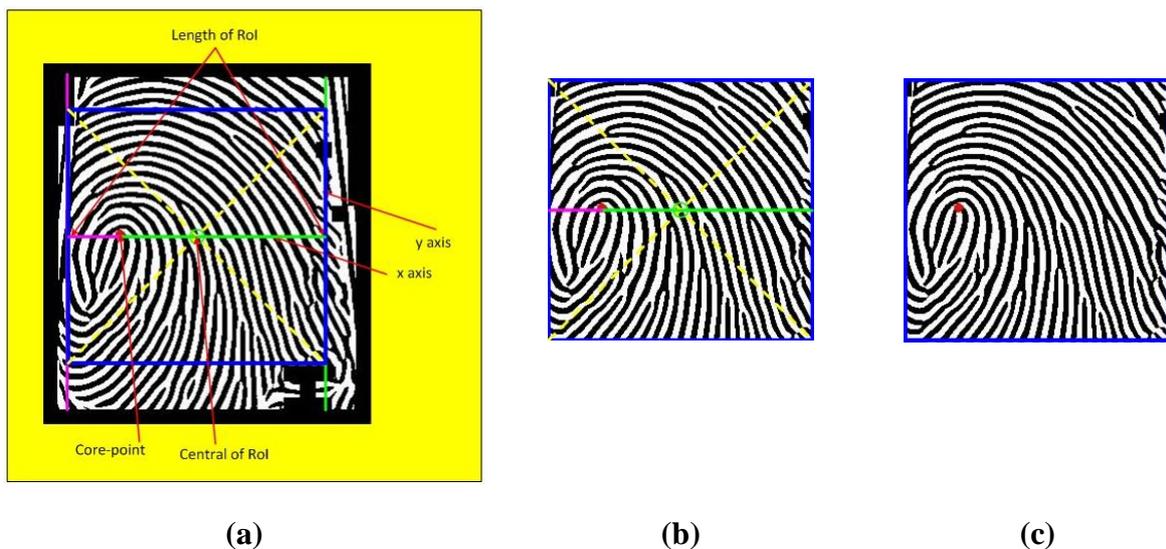
In this research, the core-point is the key to moving to the next steps of fingerprint processing. The core-point is required to select a particular region used in extracting the fingerprint features and in producing a cancellable template. Moreover, the core-point is the main requirement for classifying each fingerprint into a classification type. The core-point is required both in fingerprint classification and fingerprint matching using either the spatial domain [97] or a transformed domain [98], even though the precise core position is rarely

correct in a poor quality fingerprint. There are two techniques used to find the core position: the geometry of region technique and the detection of curvature technique.

In this research, in addition to implement these two approaches, the accuracy of core point identification is optimized by considering a pattern analysis of the ridge frequency and ridge orientation processes. The intersection pattern on these processes directs the identification system to analyse the position of the core by determining a peak-sharp pattern from the spotted area.

## 5.4. RoI

The region of interest procedure is utilized to select a full-information area of a fingerprint by positioning the core-point as a reference point to cover all the features which exist in the fingerprint image, which is based on several requirements as follows:



**Figure 5.1. RoI procedures for fingerprint image with an un-centred core-point**



## 5.5. Fingerprint Classification

Fingerprint classification is needed to decrease time consumption in the authentication step. In the authentication process, a query fingerprint will be checked by comparing it with all the fingerprints in the database. If the database is very large, this step can become a “bottleneck” in terms of speed. This would not be acceptable in a busy online application such as a bank, an office, and in terms of security. Therefore, the classification step assists systems to reduce the number of fingerprints that need to be authenticated.

The unusual distribution of fingerprint classes based on human interpretation will then decrease the efficiency of the fingerprint classification process. Instead of combining the fingerprint based on its visual appearance to generate more classes, such as tented, arc tented, right loop, left loop, and whorl; a classification scheme will be consistently distributed to the same classes. This scheme can basically be implemented in the long term, as a result of different impressions from the same fingerprint. However, there are fingerprints that always can be separated without a consideration of the quality of the database, although they are located near the classification boundary. In the end, these fingerprints are misclassified due to the wide variation of different impressions over the same fingerprints. To overcome this issue, the fingerprints are not pre-classified; however, they are associated with the vectors of the numerical features. In addition, the classes formed will be given a query fingerprint by regaining part of a fingerprint that has a feature of vectors in the database, in which the database has proximity to the query fingerprint. This approach is also called continuous classification [19], [75], [99]. Field orientation is commonly used in building the vectors of the numerical features containing local orientations [80], [99], [87], [88]. Furthermore, the average range of the fingerprint is also used as an assisting feature in some studies [75], [77].

In this research, the tented arch (TA) and core position on the fingerprint are used as requirements to decide which group the fingerprint belongs to. To improve accuracy, the direction of the looping furrow is determined to anticipate that the original fingerprint image does not have a core or that the core is undetected along the process. This step is maximized by using another approach, using ridge frequency and ridge direction, whilst the TA is just an additional requirement. The ridge orientation step helps the system to recognize the direction of the furrow. Meanwhile, the ridge frequency step is used to pattern the orientation of the fingerprint ridge using a likelihood approach.

## 5.6. Minutiae Extraction

Minutiae are one of the fingerprint features, and the minutiae extraction process has two distinctive characteristics, bifurcations and end-point characteristics. Bifurcations can be obtained if one of the fingerprint ridges meets the other two in a node. Meanwhile, the end-point is counted when the ridge plot has discontinued. In order to extract minutiae from the enhanced fingerprint image, a method that is commonly used is the crossing number (CN) concept [100], [101], [102].



the CN value for the pixel ridge, the pixel from the new image can then be classified based on of its CN value.

**Table 5.1. Properties of CN**

Crossing Number	Properties
0	Isolated point
1	Ridge ending point
2	Continuing ridge point
3	Bifurcation point
4	Crossing point

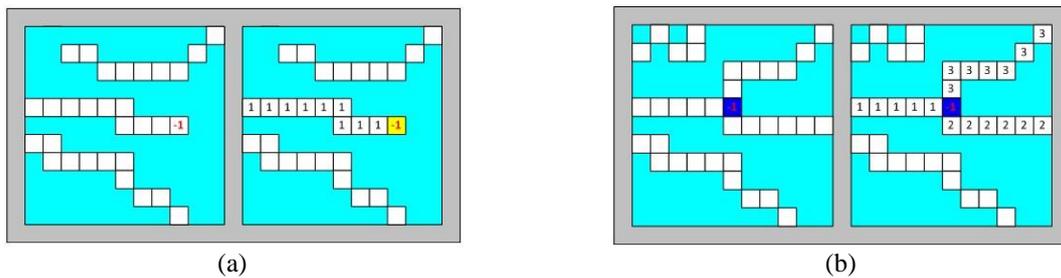


Figure 5.5. The candidate of ridge ending and ridge bifurcation (illustration using the properties of CN)

## 5.7. Experimental Results

In this research, three different databases are used to check to what extent the algorithm is appropriate to be implemented. Those databases are: FVC 2002, DB1\_B to DB4\_B; FVC 2004, DB1\_B to DB4\_B; and BRC, DBI/DBII/Training/Test. The results are as follows.

### 5.7.1. FVC 2002 Database

The FVC 2002 database provides four different types of fingerprint image from three different scanners and the SFinGE synthetic generator to collect fingerprint data as shown in the following table.

**Table 5.2. FVC 2002 Scanners/Technologies for Each Database**

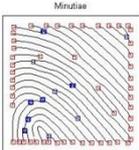
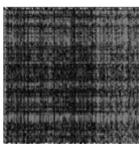
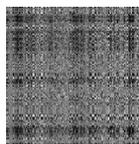
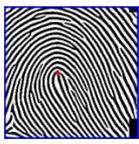
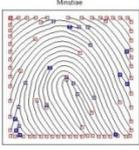
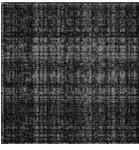
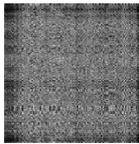
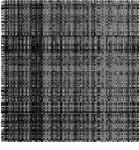
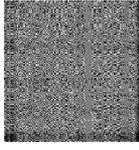
Database	Technology Used	Scanner Used	Image Size (Resolution)
DB1	Optical	Identix TouchView II	388x374 (500 dpi)
DB2	Optical	Biometrika FX2000	296x560 (569 dpi)
DB3	Capacitive	Precise Biometrics 100 SC	300x300 (500 dpi)
DB4	Synthetic	SFinGE v2.51	288x384 (500 dpi)

In FVC2002, each database has 10 different fingerprints from 10 different individuals, which for each fingerprint consists of eight different acquisition processes. Two requirements are implemented along with the collection process to manage a similar result for every volunteer, which is a maximum rotation of not more than 35 degrees and a non-null overlap between any two impressions of the same finger.

For this research, one fingerprint from each database was randomly selected to compare with the results from the implemented fingerprint processes. The processes are fingerprint enhancement, core-point identification, RoI, fingerprint classification, minutiae extraction, the cancellable fingerprint from an enhanced-RoI input, and a cancellable fingerprint of the minutiae feature. The fingerprint enhancement step is required to obtain an enhanced fingerprint input with the aim of generating a cancellable fingerprint. The

enhancement process reduces noise and unexpected information contained in the fingerprint. Core point identification is needed as a reference point in the RoI step and as one requirement in the fingerprint classification process. Meanwhile, the RoI is required because a certain form of fingerprint is needed as an input for the cancellable process.

**Table 5.3. Results for Fingerprint images of the FVC2002 database**

	Original Image	RoI	Classification	Minutia Extraction	Cancellable Template	Cancellable using Minutiae
DB1 101_1			Right Loop			
DB2 106_3			Right Loop			
DB3 107_6			Whorl			
DB4 103_1			Right Loop			

To make sure that the identification process of the fingerprint is not too time consuming, there is one particular requirement for the fingerprint classification. By classifying the fingerprint before transforming it into another form in the cancellable step, the fingerprint is already verified. Consequently, the scanning process for all the fingerprints in the database is not required. Meanwhile, the minutiae extraction process is conducted as well to generate the cancellable template.

### 5.7.2. Database FVC 2004

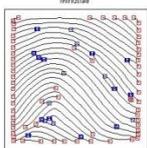
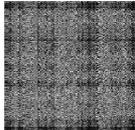
Similar to the FVC2002, the FVC2004 database has four types of database as well. These databases are collected using three commercially available scanners and a synthetic generator SFinGe.

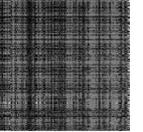
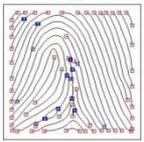
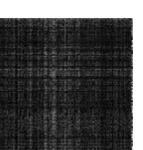
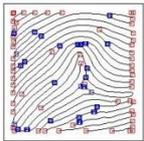
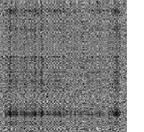
**Table 5.4. FVC 2004 Scanners/Technologies for Each Database**

Database	Technology Used	Scanner Used	Image Size (Resolution)	Fingerprint Condition
DB1	Optical	CrossMatch V300	600x480 (500 dpi)	Dried
DB2	Optical	Digital Persona U.are.U 4000	328x364 (500 dpi)	Dried
DB3	Thermal Sweeping	Atmel FingerChip	300x480 (512 dpi)	Moistened
DB4	Synthetic Generator	SFinGE v3.0	288x384 (about 500 dpi)	Moistened

The same processing steps are implemented for this FVC2002 database. The results of the fingerprint processes are as follows.

**Table 5.5. Results for Fingerprint images of the FVC2004 database**

	Original Image	RoI	Classification	Minutiae Extraction	Cancellable Template	Cancellable using Minutiae
DB1 101_2			Arch			

DB2 103_5			Whorl			
DB3 105_4			Left Loop			
DB4 107_5			Tented Arch			

### 5.7.3. Database BRC

The BRC database contains two databases, DBI and DBII. DBI consists of a small training dataset and a large test dataset. The following table provides detailed information of these databases.

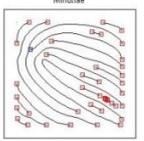
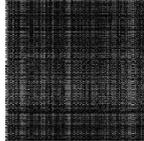
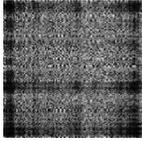
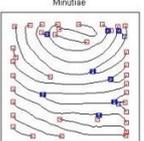
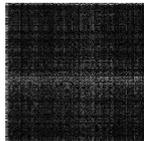
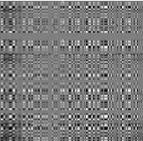
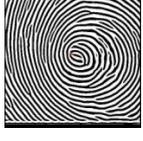
**Table 5.6. BRC database detail information**

Database	Resolution	Image Size	#Fingers	#Images per finger per session	#Images
DBI: Training	~1,200 dpi	320x240	35	3	210
DBI: Test	~1,200 dpi	320x240	148	5	1,480
DBII	~1,200 dpi	640x480	148	5	1,480

The DBI database has an image size smaller than the two other databases. Therefore, several images do not exhibit the core point and tented arch in the same appearance of the image. Accordingly, the implementation of the Galton-Henry algorithm [78], [79] in the fingerprint classification step cannot be performed because this approach requires the core

point and tented arch to appear concurrently. Consequently, a new approach is proposed to classify fingerprints in the databases.

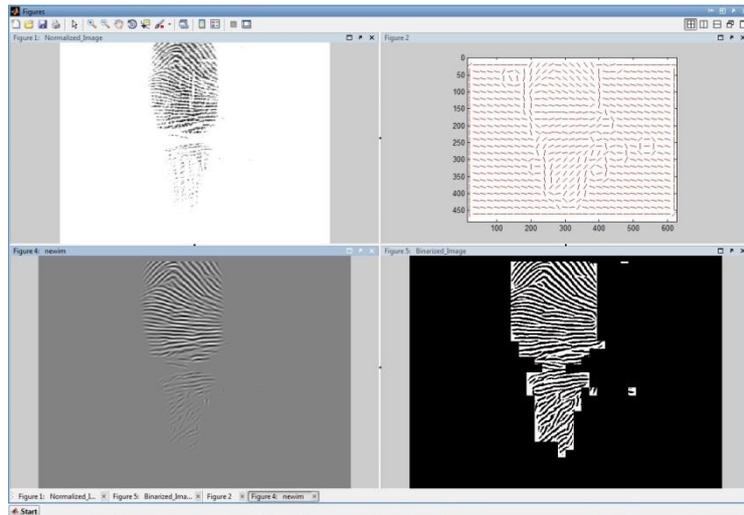
**Table 5.7. Results for fingerprint images of BRC databases**

	Original Image	RoI	Classification	Minutiae Extraction	Cancellable Template	Cancellable using Minutiae
DBI Test 16_2_1			Left Loop			
DBI Training			Whorl			
DBII 3_2_1			Whorl			

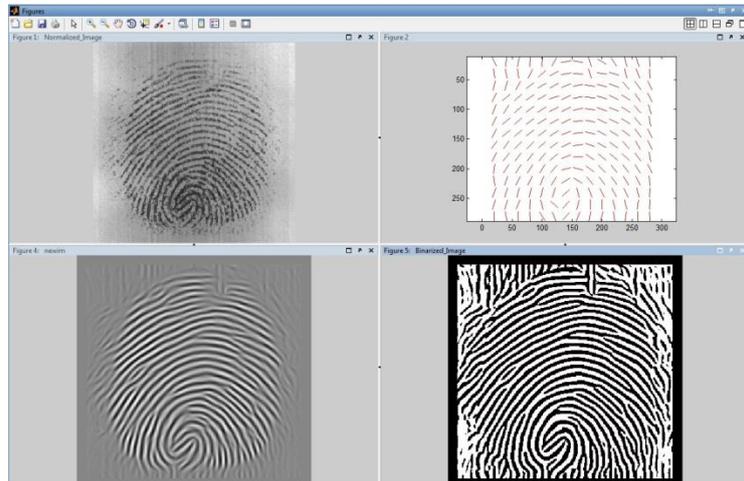
## 5.8. Discussion

From the experimental results shown in Tables 5.3.; 5.5.; and 5.7., it can be seen that the fingerprint enhancement step can improve the quality of the fingerprint by removing noise (FVC2004/DB3\_B/105\_3), sharpening ridges (FVC2002/DB2\_B/106\_3), and confirming ridge/valley patterns (FVC2004/DB4\_B/107\_5). The proposed enhancement approach is able to interpret a disconnect ridge caused by a scar in the normalization function (as shown in Figure 5.7). This function identifies the ridge regions of a fingerprint image and returns a mask identifying this region. It also normalises the intensity values of the image so that the ridge regions have zero mean and a unit standard deviation. This function breaks the

image up into blocks of size  $b \times b$  and evaluates the standard deviation in each region. If the standard deviation is above the threshold it is deemed part of the fingerprint. Note that the image is normalised to have a zero mean and unit standard deviation prior to performing this process, so that the threshold specified is relative to a unit standard deviation.



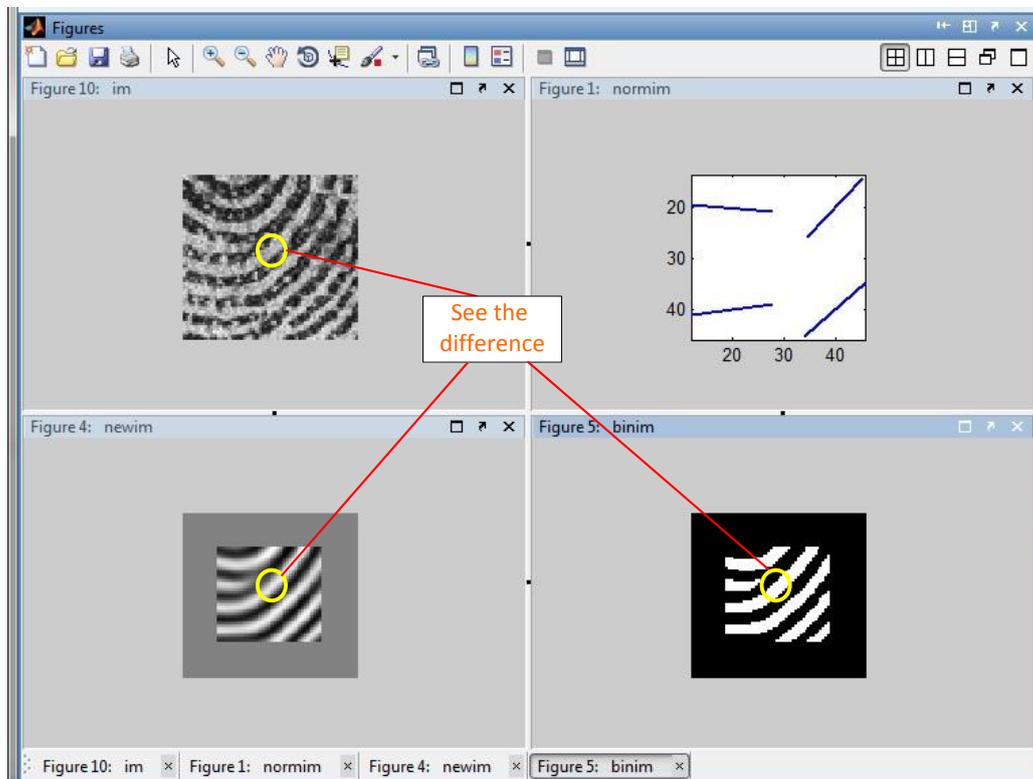
(a)



(b)

**Figure 5.6. Enhancement process results for:**  
**(a) fingerprint 101\_1 of FVC2004 DB1\_B database; (b) fingerprint 104\_8 of FVC2002 DB1\_B database;**  
**Up-left : original image**  
**Up-right : ridge orientation**  
**Down-left: filter applying for enhancing the ridge pattern**  
**Down-right: enhancement result**

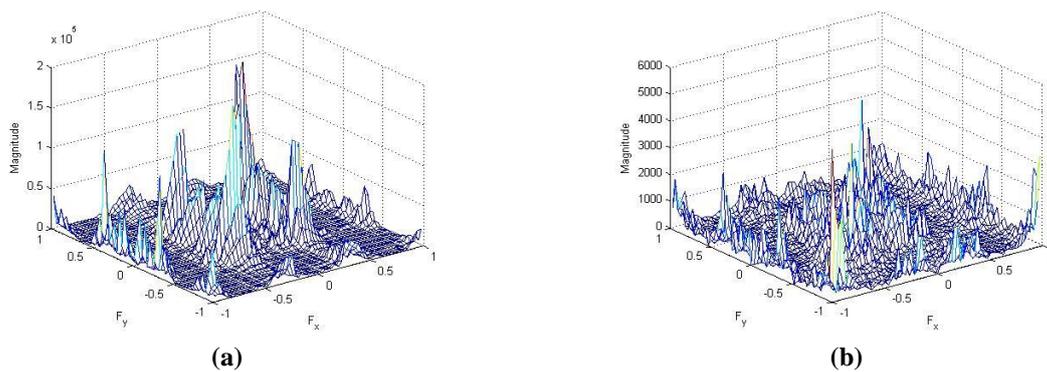
Therefore, it is clear that the improvement in the quality of the fingerprint for the all three databases is significantly reliable. Dividing images into blocks and determining the standard deviation for each block is an essential step in the decision to predict the pattern of ridges and valleys. However, this approach does not proceed if the fingerprint shows damage with scattered scratches or is stacked with another image (Figure 5.6. (b)). Moreover, the enhancement process is useful for making sure that all the fingerprint features are established in the next step. For instance, in a cancellable fingerprint implementation, an enhanced fingerprint can ensure that each pixel of the fingerprint has a precise value. Thus, if the cancellable algorithm using matrices operations is implemented, there is no pixel aversion to avoid a false matching process.



**Figure 5.7.** the enhancement process omits the noise in the original fingerprint image

An enhanced result is expected to avoid misdetection of the fingerprint features and a mismatch in the authentication stage. The improved result is counted as well in generating the cancellable fingerprint, especially the matrices operations approach. In the early proposed research for the cancellable fingerprint, it is mentioned that the enhancement process for the fingerprint is required to avoid an additional unexpected pixel in the cancellable template, as shown in Figure 5.7. This noise definitely has an effect during the confirmation step of an enquiry fingerprint.

Furthermore, as shown by the surface pattern graphic below, it can be observed that noise in the original fingerprint is reduced after the enhancing procedure. When the enhancement process is not used, the surface graphic illustrates various elements on the fingerprint. Meanwhile, after enhancement, the value on the surface of the fingerprint is identical and only patterns of the fingerprint exist on the surface.



**Figure 5.8. Comparison results between an original fingerprint (a) and an enhanced fingerprint; (b) above graphics are for surface pattern whilst bellows are for frequency.**

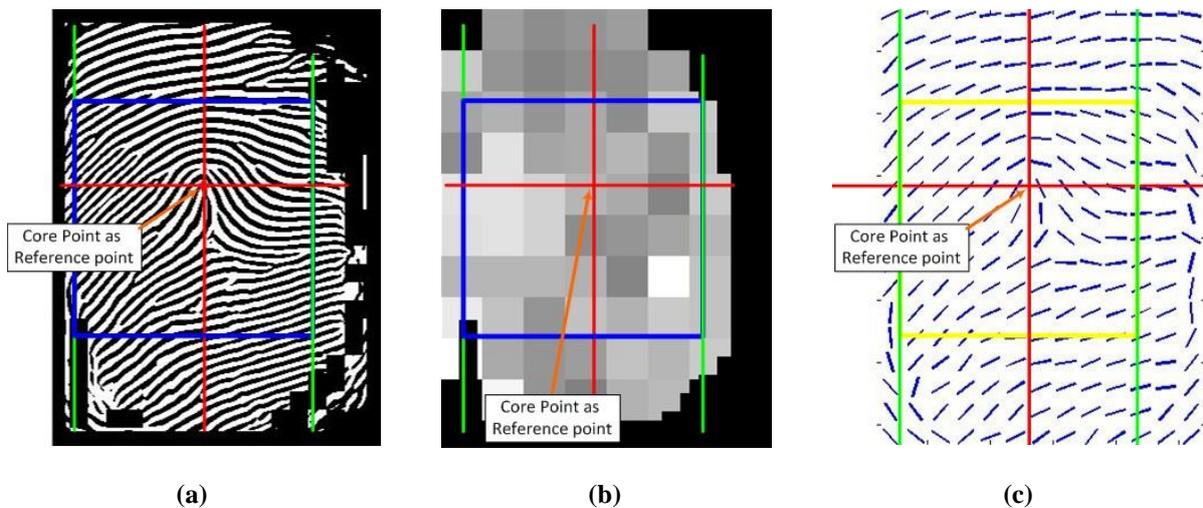
Based on the results from the core-point step, in a special case, to find the core of the fingerprint image of one database; BRC DBII image 3\_2\_1.jpg; the region of interest (RoI) is required to avoid detecting a false core-point. Initially, the RoI is needed to generate a square-form fingerprint image in generating the cancellable fingerprint using matrices operations. In this research, the stage when the RoI is implemented is after the core-point has been detected as a reference point and when a region as a certain working area should be chosen to either extract the fingerprint features or generate a cancellable fingerprint.



**Figure 5.9. Core-point identification result for**  
**(a) Without fingerprint pre-processing step**  
**(b) With fingerprint pre-processing step**

As mentioned earlier, the RoI aims to select a particular area of the fingerprint to avoid noise and to support the generation of the cancellable fingerprint, which is required in a square form of the matrix/image. From the table of results for each of the databases above, it can be seen that the RoI process reduces the coverage area of the fingerprint. This means that the RoI stage can omit several features of the fingerprint. However, the RoI experiment and two previous experiments, fingerprint enhancement and core-point detection, all demonstrate that selecting a certain particular region of the fingerprint is valuable in reducing unimportant areas or features of the fingerprint. By using the core point as a reference point for the RoI process, this ensures that the requirements are met for the next steps: fingerprint classification (needed for core-point and delta) and cancellable fingerprint (square form input image).

In this RoI stage, this research proposes a new approach to selecting a particular region. As mentioned earlier, the core-point is utilized as a reference point. Starting from this point, a horizontal or vertical line is stretched to the end of an area, which has a very dense ridges frequency and orientation pattern. This line is the length of the square form area of the fingerprint. The process is shown as Figure. 5.10.



**Figure 5.10. Step process of RoI;**

**(a) enhanced fingerprint with core-point; (b) ridge frequency (each block illustrate the dense of the ridge of fingerprint); (c) ridge orientation (the furrow illustrate the direction of the ridge of fingerprint)**

In Figure 5.10, it is seen that the red line crosses through the core-point of the fingerprint. These lines, vertical or horizontal, will find an area filled with ridges by using ridge frequency and orientation processes. In the meantime, the green lines are the end-area that contains the densely populated ridges. Moreover, both these green lines will be the length of the square RoI, as illustrated by the blue rectangle.

Furthermore, for fingerprint classification, the process is implemented using three different benchmark databases, the FVC2002, the FVC2004 and the BRC DBI. Based on the

examples of the five commonly used fingerprint classes under the Galton-Henry classification scheme, the classification results for the three databases are as follows.

a. FVC2002

In this database, there are 320 fingerprints divided into four different sub-databases, which each sub-databases consist of 10 types of fingerprints from 10 different individuals. Each fingerprint has 8 different acquisitions of a fingerprint.

**Table 5.8. Fingerprint Classification for the FVC2002 Database under the Galton-Henry Classification Scheme**

No.	Type of Classification	Percentage
1.	Arch	0.00
2.	Tented Arch	0.00
3.	Left Loop	10.31
4.	Right Loop	18.44
5.	Whorl	15.31
6.	Twin Loop Whorl	7.19

Meanwhile, the percentage of the classification based on the existence of the fingerprint type is as follows.

**Table 5.9. Fingerprint Classification for the FVC2002 Database based on the Existence of the Fingerprint**

No.	Type of Classification	Percentage
1.	Classified	51.25
2.	Unclassified	5.94
3.	Indicated as Left/Right Loop	41.56
4.	False Classification	1.25

b. FVC2004

This database has the same division and total number of fingerprints as FVC2002.

**Table 5.10. Fingerprint Classification for the FVC2004 Database under the Galton-Henry Classification Scheme**

No.	Type of Classification	Percentage
1.	Arch	2.50
2.	Tented Arch	2.50
3.	Left Loop	16.87
4.	Right Loop	5.31
5.	Whorl	21.87
6.	Twin Loop Whorl	10.00

Meanwhile, the percentage of the classification based on the existence of the fingerprint type is as follows.

**Table 5.11. Fingerprint Classification for the FVC2004 Database based on the Existence of the Fingerprint**

No.	Type of Classification	Percentage
1.	Classified	59.06
2.	Unclassified	1.56
3.	Indicated as Left/Right Loop	35.94
4.	False Classification	3.44

c. BRC DBI

Allotment in the BRC database is different from that in the two previous databases.

This database has 1480 types of fingerprints, which are divided into two different sub types for each type and five different fingerprints in one sub-type.

**Table 5.12. Fingerprint Classification for the BRC DBI-Test Database under the Galton-Henry Classification Scheme plus Four New Types of Fingerprint**

No.	Type of Classification	Percentage
1.	Arch	2.57
2.	Tented Arch	0.00
3.	Left Loop	1.89
4.	Right Loop	1.01
5.	Whorl	12.43
6.	Twin Loop Whorl	12.91
7.	Type 1 (Microphone)	0.68
8.	Type 2 (Solar Whorl)	2.09
9.	Type 3 (Closed-Left Loop)	1.15
10.	Type 4 (Loop-Whorl-Arch)	0.47

The percentage of the classification based on the existence of the fingerprint type is as follows.

**Table 5.13. Fingerprint Classification for the BRC DBI-Test Database based on the Existence of the Fingerprint**

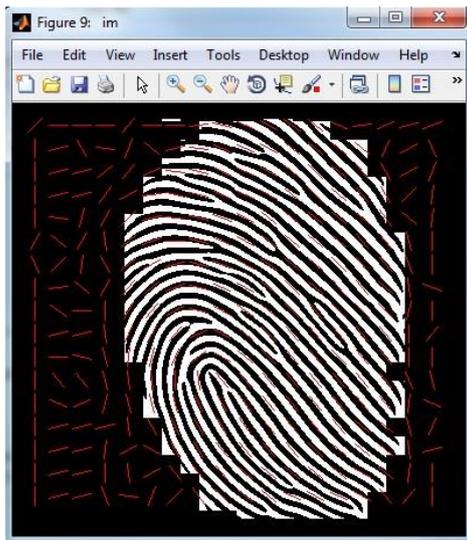
No.	Type of Classification	Percentage
1.	Classified	34.80
2.	Unclassified	17.30
3.	Indicated as Left/Right Loop	36.82
4.	False Classification	11.08

The classification process is conducted by implementing the fingerprint classes proposed by Henry-Galton. There are six different classes used in the Henry-Galton classification scheme which are arch, tented arch, left loop, right loop, whorl and twin loop

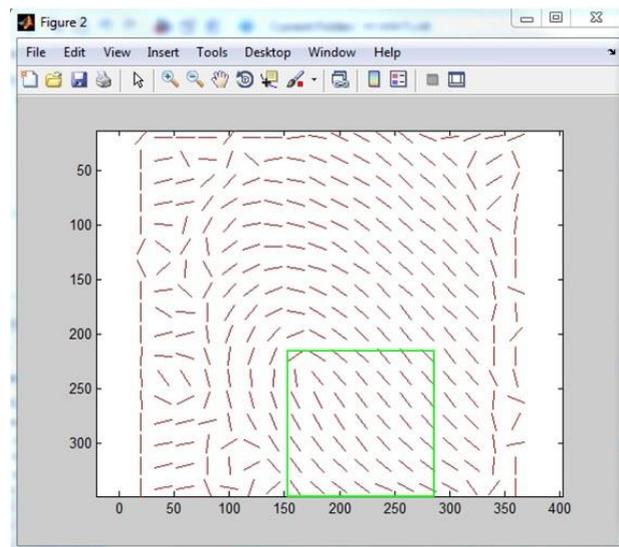
whorl. All these categories are classified based on the appearance of the core and delta of each fingerprint.

However, if this approach is used for all the benchmark databases then less than 41% of the fingerprints have the possibility of being classified, since not all of the fingerprint images have a tented arch (TA). For example, in the BRC DBI-Test, there are only 21.55% of the 1480 fingerprint images have a TA. Meanwhile, FVC2002 and FVC2004, have 37.19% and 40.31% fingerprint images respectively. Therefore, in this fingerprint classification image process, there are three requirements: core point and its number, ridge frequency and ridge direction, whilst the TA is merely an additional requirement.

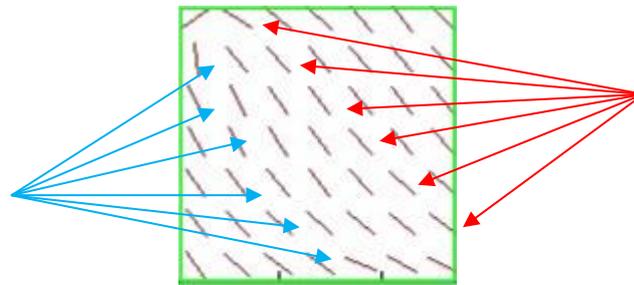
In this experiment, for the FVC2002 database, of 320 fingerprint images, only 51.25% of them are classified. Meanwhile, 5.94% are unclassified for several reasons such as no/unidentified core, no/unidentified TA, and unclear ridge/valley. Nevertheless, 35.94% of the input fingerprints are indicated as left/right loop classes and 1.25% are judged to be false classifications. This false classification happens because the fingerprints do not have some of the required conditions. For instance, some fingerprints do not have either the core or TA; therefore, it is difficult to identify the fingerprint either as left/right loop or tented arch classes. In another case, several fingerprints have an uncertain number of core points. Thus, it is classified just as a whorl class and not a twin loop whorl. Finally, a short ridge-line after the core and false-core identification can result in a false classification as well for all classes. Particularly for the likely left/right loop classes, this decision is based on the core position and upper and lower ridge furrow form and direction, as can be noted in the following pictures.



(a)



(b)



(c)

**Figure 5.11. Ridge orientation of fingerprint 101\_1.tif (FVC2002 DB1\_B); It's indicated as right loop class fingerprint**

Figure 5.11. (c) shows how a fingerprint without a TA is indicated as either a left/right loop class fingerprint. In the above fingerprint, by using the left up-angle as a predicted core-point, the pattern of ridge furrows is shown by red and blue arrows. The ridge pattern shown by the red arrow is straight and to the right-hand side, whilst the other side illustrated by the blue arrow is a curved line and to the left-hand side. Thus, this fingerprint is likely to be a right loop class fingerprint, and vice versa.

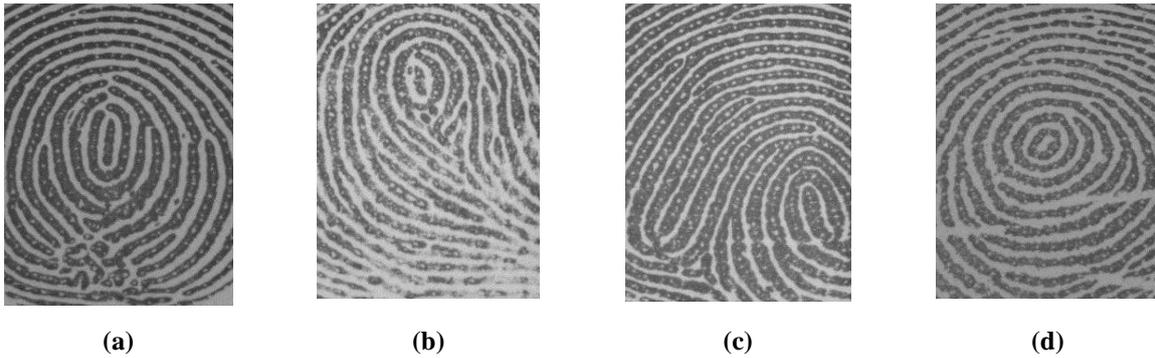
Furthermore, for FVC2004, as shown in Table 3.7., the percentage of classified fingerprints is slightly higher than for FVC2002. This is because the fingerprint input size in FVC2004 is bigger, so that fingerprint details like the core and TA are better covered than in FVC2002. Nevertheless, since the acquisition quality of FVC2004 is lower than 2002, the percentage of false classifications in FVC2004 is higher than in FVC2002.

Meanwhile, in the BRC DBI-Test case, as the size of the fingerprints is smaller than in the two previous databases, it does not provide enough detailed information to classify the fingerprint core, TA and sufficient ridge length after the core. This causes the percentage of false classifications and unclassified fingerprint to be higher than with the two other databases, as shown by the Table 5.14.

**Table 5.14. The comparison results of three different databases in terms of classified, unclassified, indicated as left/right loop and a false classification decision.**

No.	Classification Decision	FVC2002	FVC2004	BRC DBI Test
		As a percentage		
1.	Classified	51.25	59.06	34.8
2.	Unclassified	5.94	1.56	17.3
3.	Indicated as left/right loop	41.56	35.94	36.82
4.	False classification	1.25	3.44	11.08

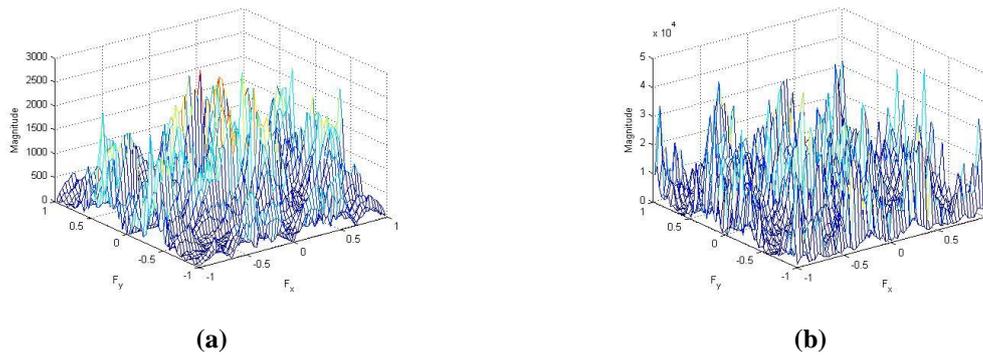
However, in this database, it is found four new fingerprint types are found as follows.



**Figure 5.12. Indicated as a new type of fingerprint (beside Henry-Galton fingerprint classes)**

In summary, the fingerprint classification process is influenced by the quality and the feature of the fingerprint. If the fingerprint acquisition provides a superior quality image, or at least the image enhancement step improves the quality, then the detailed information required to classify the fingerprint as well as for the covered region is available. Moreover, to improve the number of classified fingerprints, the use of the tented arch (TA) as a requirement can be maximized by using instead the ridge frequency and ridge direction, so that the TA is just an additional requirement.

In the feature extraction step, the experiment still uses three different benchmark databases. The results demonstrate that the proposed extraction approach works well for all the databases. It can be seen that the algorithm progressively separates each type of minutiae; bifurcation (blue square symbols) and end point (red square symbols), and removes the false minutiae as well. However, it is recognized further that this algorithm has to be improved to obtain a higher accuracy results for all the different databases. The drawback is that this approach still counts the boundaries of the input as part of the minutiae extraction. This “additional minutiae” will increase the threshold error level in the authentication step.



**Figure 5.13. Frequency Display for Cancellable Result of Fingerprint 107\_6 of Database 2002 DB3**  
**(a) For an enhanced fingerprint input**  
**(b) For minutiae input**

Finally, in this research, minutiae features are determined as an input to generate the cancellable template. This idea has the basis that minutiae are already an unknown object and information for the impostor. When the minutiae comparing to a fingerprint image, the minutiae are initially only coloured dots which are displayed without the fingerprint, as shown in Figure 5.13.

## 5.9. Summary

In generating cancellable fingerprints, there are several steps that are required. Firstly, enhancement is required to improve the quality of the fingerprint. A superior enhanced feature will make large amounts of information possible such as minutiae, core point, and fingerprint classification. The presence of this information is very important because, in this cancellable approach, there is a step where some of the parts will be modified or reduced.

It is possible to use minutiae as an input to generate the cancellable template feature. The information about bifurcations and end points that is illustrated by the coloured dots can deceive an impostor as the minutiae do not look like a fingerprint. This helps us to implement either the second or the third method for the cancellable research outline described in the previous chapter, so as to generate the cancellable feature.

To obtain a dependable cancellable feature, several fingerprint processes are required: fingerprint enhancement, core-point identification, region of interest (RoI), fingerprint classification and minutiae extraction. Based on the results from all the experiments, the following conclusions can be drawn:

(1) Fingerprint enhancement is required to produce a clear input for all the subsequent fingerprint processes. For example, an enhanced fingerprint provides a clear input image to avoid a false core-point detection and false minutiae extraction. Moreover, a fingerprint input free of noise is useful to avoid establishing an unimportant pixel in a cancellable fingerprint template by using matrices operations.

(2) In this research, the core-point detection approach is not only appropriate for one type of database. It can be implemented with different types of databases. This improvement in results is achieved if the input is an enhanced image. Otherwise, if a poor quality image becomes the input, the proposed approach detects a false core-point. As the core-point is utilized in the RoI and fingerprint classification steps, this result has an impact to achieve a progressive result and vice versa.

(3) A novel approach is proposed to select a particular area in the RoI step, in order to accommodate the needs of a square input form for the cancellable fingerprint and the need to omit unimportant areas for the minutiae extraction step. Even though the RoI stage reduces

the area of the fingerprint, this step is required so that noise in the fingerprint image can be eliminated.

(4) Minutiae extraction gives an alternative possibility for use as an input for the cancellable fingerprint template, given that its appearance is not like an initial fingerprint. Moreover, minutiae information describes common data differently from mere fingerprint data. Based on these points, the performance evaluation of all applications is determined in the following chapter to achieve better results. Furthermore, the idea of using minutiae extraction as an input to generate a cancellable template is also analyzed.

# Chapter 6

## 6. Performance Analysis

### 6.1. Introduction

The assessment of reliability in a biometric system cannot be separated from performance evaluation. Each approach implemented in biometrics, such as fingerprints will obviously provide a different result depending on the type of database utilized in the research. Previous researchers have proven that the performance of the matcher drastically decreases when the fingerprints to be compared originated from sensors with different resolutions [104]. The performance of the method proposed here is analyzed using eleven different databases which have different sizes, resolutions and characteristics, which are the FVC2002 (databases 1, 2, 3, and 4), FVC2004 (databases 1, 2, 3, and 4), and BRC (database I, test and training; and database II). For the FVC2002 and FVC2004 databases, there are ten different fingerprints with eight different acquisition processes. Meanwhile for the BRC database, there are ten kinds of fingerprints with six different enrolments.

### 6.2. Error Rates

The authentication step evaluates the ability of the proposed method to authenticate whether the inputs of the fingerprint are a genuine owner or an impostor. This categorizing process validates the genuine nature of the fingerprint by implementing various steps, as a score for both an established fingerprint and the input fingerprint as an enquiry fingerprint.

The first step is by directing the the input into its fingerprint classification group to shortage the identification process. Next is by calculating the distance between core and tent arch (TA) of the fingerprint. The third step is by scoring a minimum and maximum distances of matrix values of minutiae between an original fingerprint registered in database and several fingerprints from the same owner as information to calculate the distance value of each pixel of the fingerprint, so that variant possibility of a genuine fingerprint can be decided later even when the acquisition process of each fingerprint is taken differently. The next step is by evaluating the scoring of minimum and maximum distances of matrices values of minutiae between the genuine data and a false data to score the value to reject an input. The last step is by setting a cut-off value of accepted and rejected decision as a result of the third and the fourth steps.

The evaluation starts by determining an equal error rate (EER) for each database. This characteristic is a point where two types of rates, the genuine accepted rate (GAR) and false acceptance rate (FAR) intersect with the same value. The GAR is the percentage of genuine fingerprint features that are accepted during an authentication step. Meanwhile, the FAR is the percentage of impostor fingerprint features that are accepted in the same step.

Furthermore, in term of recognizing the minimum level of FAR, a threshold for the acceptance rate is assigned which varies from 0 to 100 per cent with interval of 5 per cent. The level chosen is named as the cut-off point. This means that a fingerprint would be rejected if the acceptance level was higher. The cut-off level for each database would be different depending on the quality of the original fingerprint images.

In the FVC2002 DB (1, 2, 3, 4) and FVC2004 DB (1, 2, 3, 4), there are ten different owners of fingerprints each of which consists of eight different acquisition directions. This means that there are 80 types of fingerprints in this database, where one of those is selected as

the owner represented in the database. From the 79 fingerprints which are left, only seven are categorized into accepted, rejected, false accepted, and false rejected, while the remaining 72 are completely rejected and are not included in those categories as a result of the implementation of the classification step. Seven fingerprints are accepted since their acceptance rates are higher than the cut-off value.

This step not only saves time during the process, but also helps the system to reduce the number of fingerprints needing to be analyzed. During this stage, an enquiry input will be grouped into its particular class so that an inappropriate fingerprint would be rejected automatically before proceeding to the matching step. Given that each fingerprint in the same database is already categorized into its own class, the percentage EERs for the databases are illustrated in the following eight tables (Tables 6.1 - 6.8).

**Table 6.1. EER values for FVC 2002 DB1**

<b>Fingerprint</b>	<b>EER</b>	<b>FAR</b>	<b>Cut-off point</b>
101	0.063	0.125	0.425
102	0.125	0.250	0.275
103	0.063	0.125	0.075
104	0.063	0.125	0.375
105	0.250	0.500	0.275
106	0.063	0.125	0.125
<b>107</b>	<b>0.063</b>	<b>0.125</b>	<b>0.475</b>
108	0.125	0.250	0.475
109	0.125	0.250	0.475
110	0.063	0.125	0.225

In Table 6.1, it can be noted that the EERs vary, with values of 0.063 and 0.125; and 0.250 for the cut-off point which varies from 0.075 to 0.475. The higher value of the cut-off

point indicates that the fingerprint is in a better condition to achieve good error rate. This means that fingerprint 107 is superior to the other fingerprint in terms of error, as it has a lower EER. Figure 6.1 demonstrates the fingerprints that are used as established input in the FVC2002DB1 database.



**Figure 6.1. Original RoI fingerprint of FVC2002DB1 used as the established database; 101 to 110 start from the top left corner and circulate clockwise.**

**Table 6.2. EER values for FVC 2002 DB2**

<b>Fingerprint</b>	<b>EER</b>	<b>FAR</b>	<b>Cut-off point</b>
101	0.125	0.250	0.375
102	0.125	0.250	0.375
103	0.063	0.125	0.275
<b>104</b>	<b>0.063</b>	<b>0.125</b>	<b>0.475</b>
105	0.063	0.125	0.325
106	0.125	0.250	0.375
107	0.063	0.125	0.375
108	0.188	0.375	0.525
109	0.063	0.125	0.125
110	0.063	0.125	0.325

Table 6.2 shows the error rates of the FVC2002DB2 database. It can be seen that fingerprint 104 has an improved position in its error rate, as it has the highest cut-off point for a better EER. Its value is the same within the DB1 database, which gives an EER of 0.063 with a cut-off point of 0.475. Figure 6.2 shows the fingerprints that are used as an established input in the FVR2002DB2 database.



**Figure 6.2. Original RoI fingerprint of FVC2002DB2 used as the established database; 101 to 110 start from the top left corner and circulate clockwise.**

**Table 6.3. EER values FVC 2002 DB3**

<b>Fingerprint</b>	<b>EER</b>	<b>FAR</b>	<b>Cut-off point</b>
101	0.063	0.125	0.075
102	0.063	0.125	0.325
103	0.188	0.375	0.425
104	0.063	0.125	0.275
105	0.063	0.125	0.075
106	0.125	0.250	0.375
<b>107</b>	<b>0.063</b>	<b>0.125</b>	<b>0.375</b>
108	0.188	0.375	0.525
109	0.188	0.375	0.325
110	0.063	0.125	0.175

For the FVC2002DB3 database, fingerprint 107 has an enhanced result in acquiring a superior error rate. It has a cut-off point of 0.375 for the lower EER of 0.063. Similarl to the DB2 database, the EERs from DB3 are spread among three values of 0.063, 0.125 and 0.188. However, the database has the highest cut-off point which is lower than those for the two previous databases. It appears that DB3 does not have a better error rate qualification than DB1 and DB2. Figure 6.3 shows the fingerprints that are used as an established input in the FVR2002DB3 database.

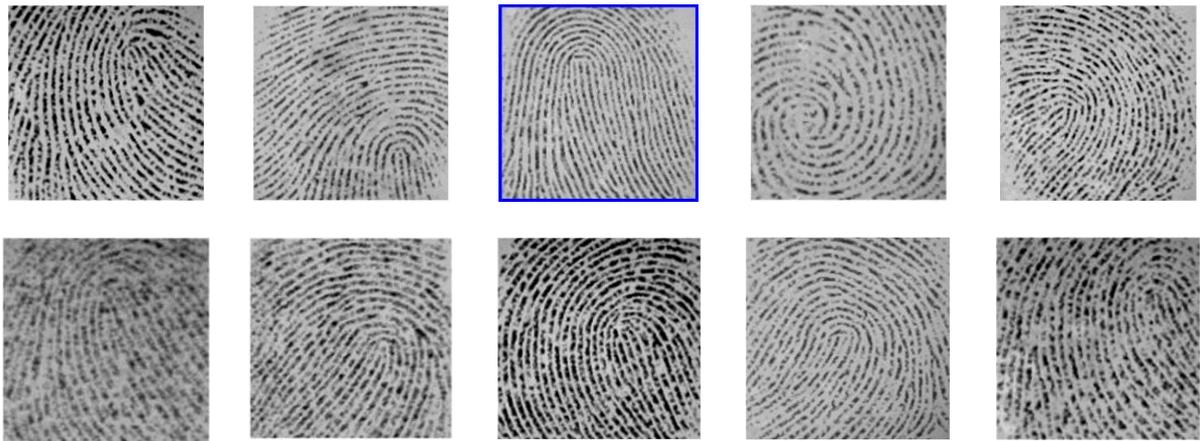


**Figure 6.3.** Original RoI fingerprint of FVC2002DB3 used as the established database; 101 to 110 start from the top left corner and circulate clockwise.

**Table 6.4.** EER values for FVC 2002 DB4

<b>Fingerprint</b>	<b>EER</b>	<b>FAR</b>	<b>Cut-off point</b>
101	0.125	0.250	0.275
102	0.125	0.250	0.325
<b>103</b>	<b>0.063</b>	<b>0.125</b>	<b>0.425</b>
104	0.063	0.125	0.225
105	0.063	0.125	0.325
106	0.063	0.125	0.075
107	0.125	0.250	0.325
108	0.125	0.250	0.325
109	0.063	0.125	0.225
110	0.063	0.125	0.125

As with the three previous databases, the FVC2002DB4 database has the lowest EER at 0.063. However, it has the lowest EERs compared with the other databases of 0.063 and 0.125. In addition, fingerprint 103 has a superior error rate compared to the others, attaining an EER of 0.063 for a 0.425 cut-off point position.



**Figure 6.4. Original RoI fingerprint of FVC2002DB4 used as the established database; 101 to 110 start from the top left corner and circulate clockwise.**

Overall, the technology used in the FVC2004 database is similar to that of the FVC2002 database, except for the DB3database. In FVC2002DB3, the technology that is used is capacitive, using a Precise Biometrics 100 SC scanner. Meanwhile, in FVC2004DB3 the technology has changed to a thermal sweeping application using an Atmel FingerChip scanner. Despite the similarity amongst the three other databases, all the databases in FVC2004 use different scanners to acquire the fingerprint.

Table 6.5. EER values for FVC 2004 DB1

<b>Fingerprint</b>	<b>EER</b>	<b>FAR</b>	<b>Cut-off point</b>
101	0.063	0.125	0.075
102	0.063	0.125	0.075
103	0.063	0.125	0.175
104	0.063	0.125	0.375
105	0.063	0.125	0.125
<b>106</b>	<b>0.063</b>	<b>0.125</b>	<b>0.525</b>
107	0.063	0.125	0.175
108	0.063	0.125	0.375
109	0.063	0.125	0.125
110	0.125	0.250	0.075

The lowest EER in FVC2004DB1 is 0.063, which is similar in all databases in FVC2002. Almost all of the fingerprints in FVC200DB1 give this EER value except for fingerprint 110. The cut-off point in this database varies from 0.075 to 0.525. Furthermore, fingerprint 106 has an improved error rate, receiving an EER of 0.063 with a cut-off point value of 0.525. Figure 6.5 demonstrates the fingerprints that are used as an established input in the FVR2004DB1 database.



Figure 6.5. Original RoI fingerprint of FVC2004DB1 used as the established database; 101 to 110 start from the top left corner and circulate clockwise.

**Table 6.6. EER values for FVC 2004 DB2**

<b>Fingerprint</b>	<b>EER</b>	<b>FAR</b>	<b>Cut-off point</b>
101	0.125	0.250	0.075
102	0.063	0.125	0.125
103	0.125	0.250	0.175
<b>104</b>	<b>0.063</b>	<b>0.125</b>	<b>0.175</b>
105	0.063	0.125	0.025
106	0.375	0.750	0.025
107	0.063	0.125	0.075
108	0.250	0.500	0.025
109	0.063	0.125	0.075
110	0.063	0.125	0.125

In table 6.6, it seems that fingerprint 104 has an enhanced error rate compared to the others with an EER of 0.063 and a 0.175 cut-off point value. Compared with the previous database, the value of the highest cut-off point of the FVC2004DB2 database is lower than the others. The noise captured on the fingerprint during the acquisition process could reduce the number of matching fingerprints. This could cause the cut-off point value to become higher. Figure 6.6 shows the fingerprints that were used as an input in the process.



**Figure 6.6. Original RoI fingerprint of FVC2004DB2 used as the established database; 101 to 110 start from the top left corner and circulate clockwise.**

**Table 6.7. EER values for FVC 2004 DB3**

<b>Fingerprint</b>	<b>EER</b>	<b>FAR</b>	<b>Cut-off point</b>
101	0.063	0.125	0.075
102	0.063	0.125	0.075
103	0.063	0.125	0.025
104	0.063	0.125	0.075
105	0.063	0.125	0.075
106	0.063	0.125	0.125
<b>107</b>	<b>0.063</b>	<b>0.125</b>	<b>0.175</b>
108	0.063	0.125	0.025
109	0.188	0.375	0.275
110	0.125	0.250	0.075

The error rate for the FVC2004DB3 database is the same as in the FVC2004DB2 database, where the EER is 0.063 and the cut-off point of 0.175. Fingerprint 107 has the best error rate. This is affected by the condition of the fingerprint from the FVC2004DB3 database, which was moistened. A moistened fingerprint produces features with various type of noise. This condition results in a number of matching fingerprints in this database. It decreases the quality of fingerprint matching in authentication as it is difficult to match the enquiry fingerprint with the established one, so that the value of the cut-off point has to be lowered to obtain a superior EER. Figure 6.7 describes the appearance and condition of fingerprints in FVC2004DB4 that were used as an input for the system.



**Figure 6.7. Original RoI fingerprint of FVC2004DB3 used as the established database; 101 to 110 start from the top left corner and circulate clockwise.**

**Table 6.8. EER values for FVC 2004 DB4**

<b>Fingerprint</b>	<b>EER</b>	<b>FAR</b>	<b>Cut-off point</b>
101	0.063	0.125	0.025
102	0.125	0.250	0.375
103	0.063	0.125	0.175
104	0.125	0.250	0.375
105	0.063	0.125	0.275
106	0.063	0.125	0.275
<b>107</b>	<b>0.063</b>	<b>0.125</b>	<b>0.325</b>
108	0.125	0.250	0.175
109	0.063	0.125	0.125
110	0.063	0.125	0.175

Although FVC2004DB4 has the same fingerprint condition as DB3 and, moreover, the cut-off point for a better error rate in DB4 is slightly higher than in DB3 ( 0.325 for DB4 and 0.175 for DB3), fingerprint 107 has a superior error rate with an EER of 0.063 and a cut-off point of 0.325. The appearance of the fingerprint inputs for the FVC2004DB4 database is shown in the Figure 6.8.



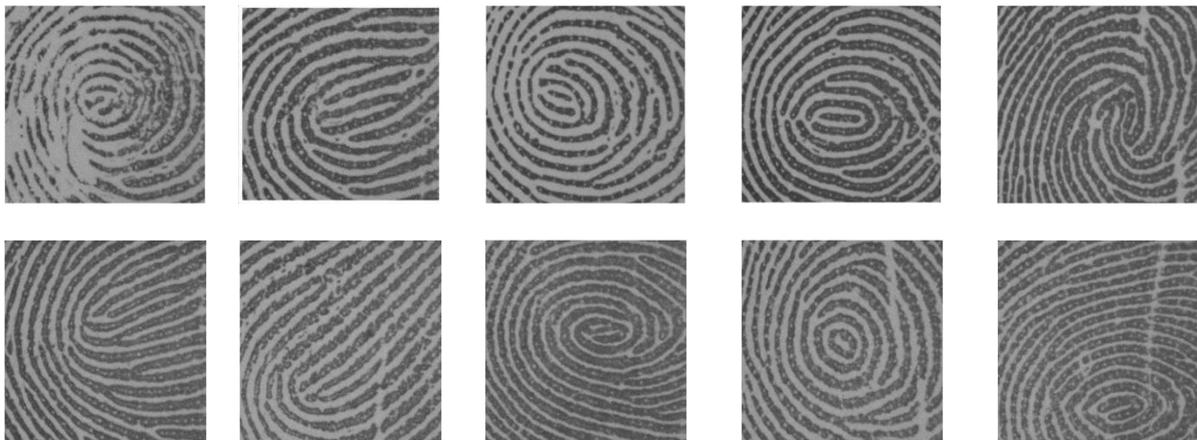
**Figure 6.8. Original RoI fingerprint of FVC2004DB4 used as the established database; 101 to 110 start from the top left corner and circulate clockwise.**

Meanwhile for the BRC family database, each of them contains sixty fingerprints in total. As with the FVCs families, these total numbers come from ten different people with each person possessing six different kinds of fingerprints. Tables 6.9 - 6.11 provide information in relation to the EER of each fingerprint in the DB1 Test database, DB1 Training and DB2.

**Table 6.9. EER values for BRC DB1 Test**

<b>Fingerprint</b>	<b>EER</b>	<b>FAR</b>	<b>Cut-off point</b>
1	0.083	0.167	0.175
2	0.250	0.500	0.825
3	0.083	0.167	0.625
4	0.083	0.167	0.425
5	0.083	0.167	0.325
<b>6</b>	<b>0.083</b>	<b>0.167</b>	<b>0.675</b>
7	0.167	0.333	0.425
8	0.167	0.333	0.625
9	0.083	0.167	0.225
10	0.333	0.500	0.775

Referring to Table 6.9, fingerprint 6 has the best error rate compared to the other fingerprints with an EER of 0.083 and a threshold value of 0.675. Overall, the BRCDB1 Test database has a better qualification of fingerprint in the matching step based on the highest cut-off point value shown in the above table, where the system could have had an acceptance of fingerprints of 100% when the threshold was assigned a matching requirement of 82.5%.



**Figure 6.9. Original RoI fingerprint of the BRCDB1Test used as the established database; 1 to 10 start from the top left corner and circulate clockwise.**

**Table 6.10. EER values for BRC DB1 Training**

<b>Fingerprint</b>	<b>EER</b>	<b>FAR</b>	<b>Cut-off point</b>
<b>6</b>	<b>0.083</b>	<b>0.167</b>	<b>0.625</b>
9	0.083	0.167	0.575
11	0.083	0.167	0.425
13	0.083	0.167	0.375
16	0.167	0.333	0.525
18	0.083	0.167	0.175
34	0.083	0.167	0.025
41	0.083	0.167	0.275
42	0.083	0.167	0.225
47	0.083	0.167	0.275

Fingerprint 6 has a better error rate in the BRCDB1Training database and also has a better cut-off point, even though it is not as good as the BRCDB1Test database. Fingerprint 6 has an EER of 0.083 and a cut-off point level of 0.625.

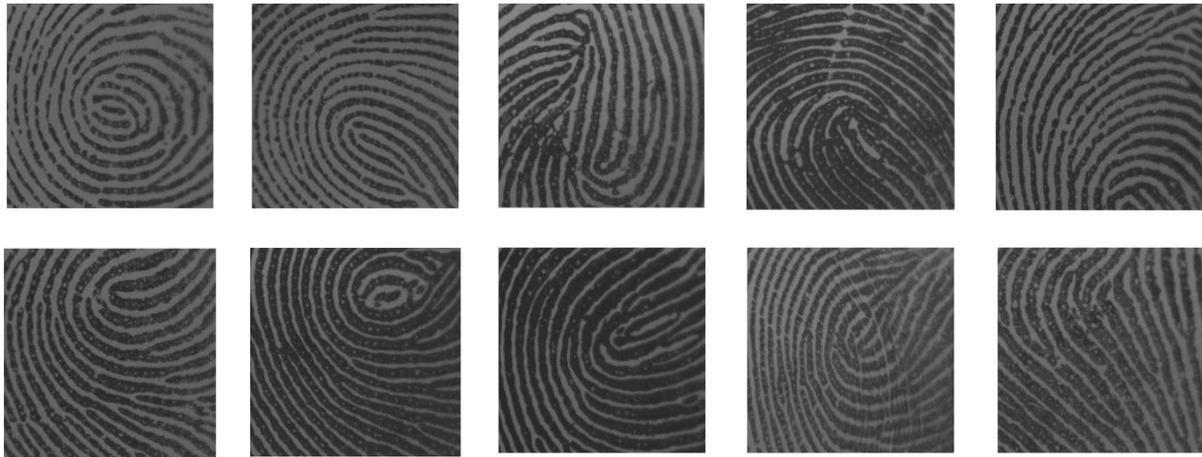
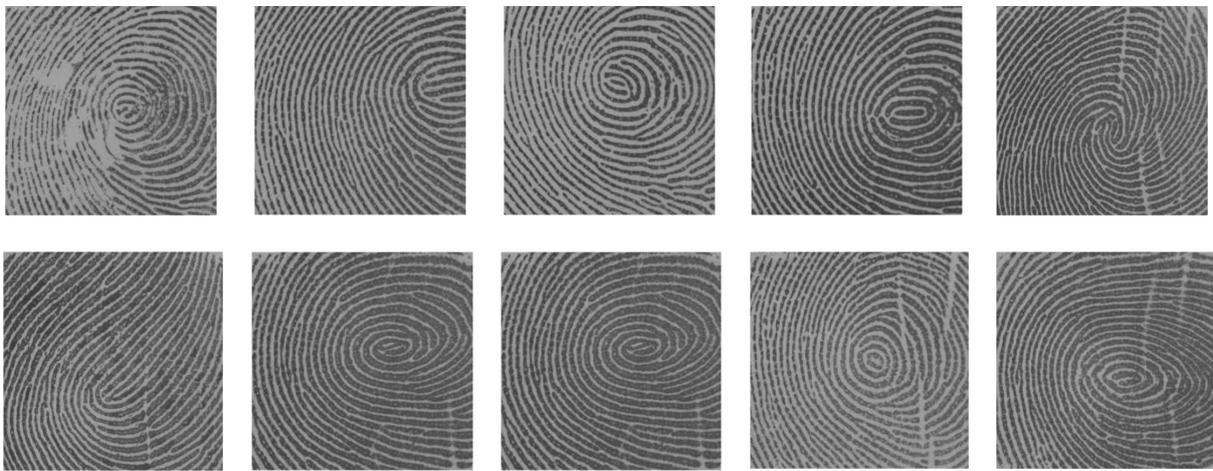


Figure 6.10. Original RoI fingerprint of the BRCDB1Training used as the established database; 6, 9, 11, 13, 16, 18, 34, 41, 42, and 47 start from the top left corner and circulate clockwise.

Table 6.11. EER values for BRC DB2

Fingerprint	EER	FAR	Cut-off point
1	0.250	0.500	0.475
2	0.167	0.333	0.825
<b>3</b>	<b>0.083</b>	<b>0.167</b>	<b>0.675</b>
4	0.083	0.167	0.425
5	0.167	0.333	0.425
6	0.167	0.333	0.625
7	0.167	0.333	0.625
8	0.083	0.167	0.525
9	0.167	0.333	0.325
10	0.083	0.167	0.225

Fingerprint 3 in the BRCDB2 database has an error rate as good as fingerprint 6 in BRCDB1Test database, with an EER of 0.083 and a cut-off point of 0.675. Moreover, based on the data from the EER and the cut-off point obtained, the BRCDB1Test database and BRCDB2 have almost similar values in quality and matching level. Both databases have the best matching rate at 82.5% and the best error rate at 0.083/0.675. Figures 6.9 and 6.11 illustrate the input of fingerprints used for both databases.



**Figure 6.11. Original RoI fingerprint of BRCDB2 used as the established database; 1 to 10 starts from the top left corner and circulate clockwise.**

### 6.3. Evaluation of Time Taken

The second issue to be evaluated is the time needed to execute the proposed algorithm. Time consumption is a critical issue to be determined given that there are two different inputs of the fingerprints adopted in generating a cancellable feature and its authentication process. This first combination of input is the cancellable step; core-point step; classification step and authentication step using an original fingerprint image. The second is the cancellable step; core-point step; classification step; RoI step and authentication step

using a cropped input. Furthermore, the total times for each combination are compared, in order to see which combination is better. The proposed approach has been tested using Intel Core i5-2430M CPU@2.40GHz; 4.00 GB installed RAM; and MATLAB version 7.10.0 (R2010a).

**Table 6.12. Time needed for the FVC 2002 database (in seconds)**

No.	Steps	Time Needed							
		DB1		DB2		DB3		DB4	
		Original	RoI	Original	RoI	Original	RoI	Original	RoI
1.	Cancellable	0.8589	0.4834	1.1610	0.5269	0.8333	0.4825	0.9826	0.4765
2.	Core-time	0.5542	0.4099	0.9232	0.4190	0.6627	0.3837	0.7814	0.3789
3.	Classification	0.7269	0.5048	0.7592	0.5255	0.6941	0.4811	0.6855	0.4751
4.	RoI		0.2316		0.2538		0.2320		0.2291
5.	Authentication	0.000187	0.000130	0.000204	0.000142	0.000187	0.000130	0.000184	0.000128
<b>Total</b>		2.140187	1.62983	2.843604	1.725342	2.190287	1.57943	2.449684	1.559728
<b>Time Different (%) (Original and RoI)</b>		23.85		39.33		27.89		36.33	

**Table 6.13. Time needed for the FVC 2004 database (in seconds)**

No.	Steps	Time Needed							
		DB1		DB2		DB3		DB4	
		Original	RoI	Original	RoI	Original	RoI	Original	RoI
1.	Cancellable	1.0951	0.4842	0.7731	0.4738	1.0568	0.4903	0.8942	0.4873
2.	Core-time	0.8709	0.3850	0.6148	0.3768	0.8218	0.3805	0.7111	0.3875
3.	Classification	0.6966	0.4829	0.6820	0.4725	0.6878	0.4772	0.7009	0.4860
4.	RoI		0.2328		0.2280		0.2357		0.2343
5.	Authentication	0.000187	0.000130	0.000183	0.000127	0.000190	0.000132	0.000188	0.000131
<b>Total</b>		2.662787	1.58503	2.070083	1.551227	2.566590	1.583832	2.306388	1.595231
<b>Time Different (%) (Original and RoI)</b>		40.47		25.06		38.29		30.84	

Tables 6.12 - 6.14 illustrate the time taken by the system to execute all of the research steps. From each table, the comparison among different sub-databases in the same database is shown to provide a different percentage between the original input and RoI input, in order to show which input can provide more efficient use of time to run all the steps.

**Table 6.14. Time needed for the BRC database (in seconds)**

No.	Steps	Time Needed					
		DB1 Test		DB1 Training		DB2	
		Original	RoI	Original	RoI	Original	RoI
1.	Cancellable	0.5049	0.4943	0.4762	0.4750	0.6159	0.5262
2.	Core-time	0.4015	0.3931	0.3787	0.3777	0.4898	0.4184
3.	Classification	0.7120	0.4929	0.6842	0.4737	0.7584	0.5247
4.	RoI		0.2380		0.2287		0.2535
5.	Authentication	0.000191	0.000133	0.000184	0.000128	0.000203	0.000142
<b>Total</b>		1.618591	1.618433	1.539284	1.555228	1.864303	1.722942
<b>Time Different (%) (Original and RoI)</b>		0.0057		-1.04		7.59	

Overall, it is obvious that the system using the RoI input consumes less time than an original input except for the BRCDB1Training database, even though this system has one more step included in the process (the RoI step). The size of the input fingerprint significantly contributes to reducing the time taken for the procedure. Table 6.15 shows the contribution of size differences to the time taken by the process.

**Table 6.15. Correlation between the size differences of the input fingerprint and time taken by the process (%)**

	DB1		DB2		DB3		DB4	
	Size	Time	Size	Time	Size	Time	Size	Time
<b>FVC2002</b>	43.13	23.85	53.95	39.33	41.11	27.89	51.21	36.32
<b>FVC2004</b>	54.86	40.47	38.08	25.06	53.38	38.29	45.30	30.84
	DB1 Test		DB1 Training		DB2			
	Size	Time	Size	Time	Size	Time		
<b>BRC</b>	1.81	0.0057	0.25	-1.04	14.04	7.59		

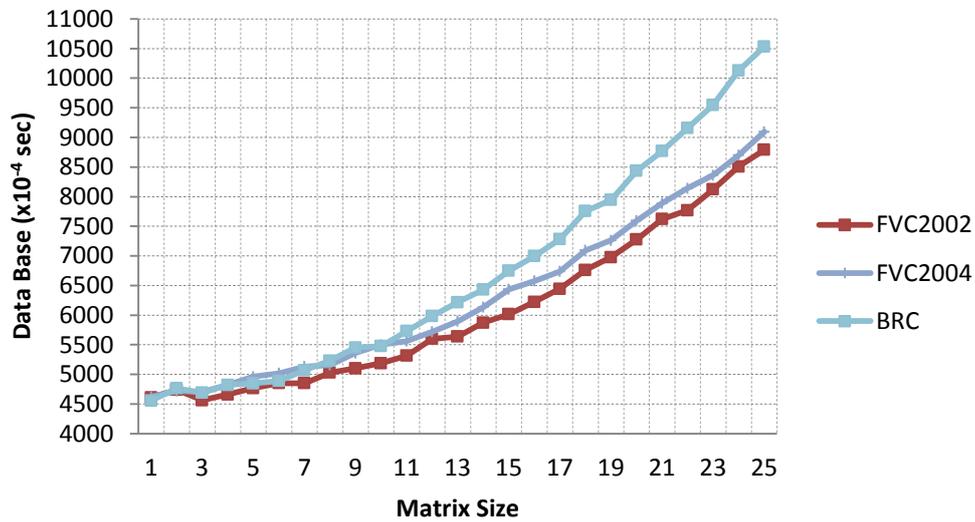
Table 6.15 clearly shows the relationship between the size of the input fingerprint and the time taken to complete all the processes. A larger input would require more time. However, in this research case, it can be argued that the size difference should not be too narrow, such as in the BRCDB1Training database, because a system that uses a fingerprint of the RoI size needs the RoI selection step in its process. This means that it would demand more time to execute the process. Nevertheless, Table 6.15 proves that this case is not a huge obstacle in this research.

## 6.4. Evaluation of Matrices Operations Requirements

### 6.4.1. The Size of the Arbitrary Matrix of the KP Operation

Another parameter considered in the performance of the system is the size of the arbitrary matrix that is used to produce a cancellable feature for the fingerprint. The reason for this is because the size of that matrix could affect the time consumed in running the process. Therefore, various in matrix size were simulated to check its influence on the time taken for the running of the process for the FVC2002, FVC2004 and BRC databases.

## Correlation of the Size of the Arbitrary Matrix and Time Taken



## Correlation of the Size of the Arbitrary Matrix and Time Taken

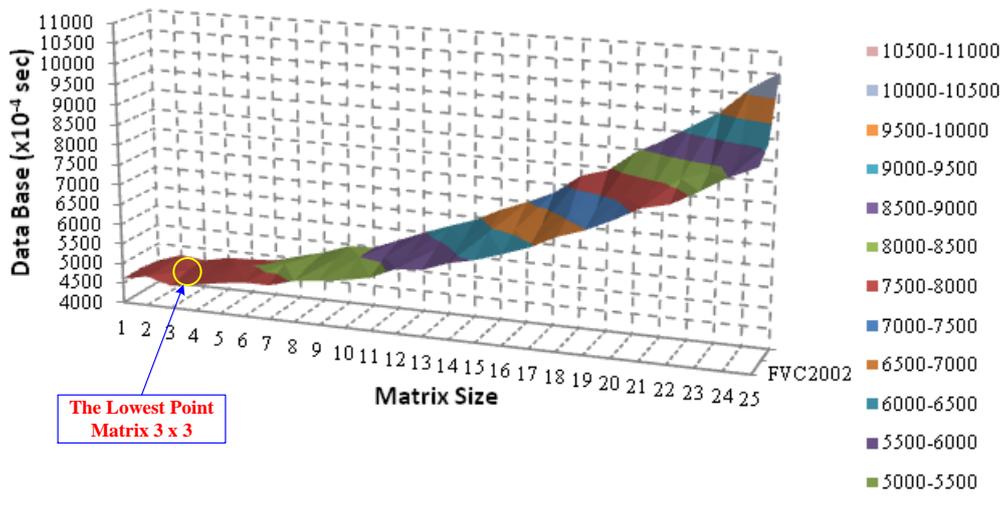


Figure 6.12. Illustrating the correlation between the size of the arbitrary matrix and time taken for the process

Figure 6.12 shows a simulation trend by increasing the size of the matrix started from  $1 \times 1$  until  $25 \times 25$  while recording the time consuming along the simulation. During the simulation, it is established that the time taken would tend to increase, in addition to there being a rise in the size of the matrix. However, at matrix  $3 \times 3$ , the trend tends to lower before rising again at matrix  $4 \times 4$ . Therefore, the size of the arbitrary matrix used in this research is matrix  $3 \times 3$ .

#### 6.4.2. The Zero Rows and Column of ERO Operation

In the ERO operation, the most important issue to be discussed is the best number of zero rows and columns needed to make sure that the cancellable template is safe from impostors. The analysis is completed by undertaking several simulations involving increasing the number of zero rows, improving the number of zero columns, and using the zero rows and columns simultaneously, while increasing the number of zero rows and columns as well. These simulations are performed starting from one until  $n/3$  rows/columns, where  $n$  is the size of the input of the fingerprint. The reason for choosing  $n/3$  as the limit to increase the number of rows and columns is because this would lose the detailed information of the fingerprint feature. Figures 6.13 – 6.20 illustrate all of the simulations completed in the research.

-13.2515	-48.5150	-62.6468	-50.0396	-16.3391	24.1932	54.9296	63.7668
14.1556	-28.0481	-57.4675	-62.1471	-40.5157	-1.9108	37.4970	62.6071
39.7504	-1.8382	-41.5896	-63.1917	-59.4876	-29.4826	12.6003	49.4918
58.7400	25.1083	-18.0617	-54.2500	-66.9095	-51.6159	-15.1277	27.3705
67.7559	47.9171	9.0100	-34.3391	-62.9618	-65.2899	-40.8292	-0.0031
65.3777	64.5113	35.1631	-8.5376	-48.4109	-68.1412	-60.0694	-27.9643
54.2384	69.3609	55.6404	18.7757	-25.8578	-59.8850	-69.6673	-51.7492
32.5657	63.1902	67.3054	43.1696	0.9109	-41.9890	-68.1936	-67.5786

**Figure 6.13. Illustration of the original feature of the fingerprint**

-13.2515	-48.5150	-62.6468	-50.0396	-16.3391	24.1932	54.9296	63.7668
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
39.7504	-1.8382	-41.5896	-63.1917	-59.4876	-29.4826	12.6003	49.4918
58.7400	25.1083	-18.0617	-54.2500	-66.9095	-51.6159	-15.1277	27.3705
67.7559	47.9171	9.0100	-34.3391	-62.9618	-65.2899	-40.8292	-0.0031
65.3777	64.5113	35.1631	-8.5376	-48.4109	-68.1412	-60.0694	-27.9643
54.2384	69.3609	55.6404	18.7757	-25.8578	-59.8850	-69.6673	-51.7492
32.5657	63.1902	67.3054	43.1696	0.9109	-41.9890	-68.1936	-67.5786

**Figure 6.14. One row of the original feature of the fingerprint replaced by zero row**

-13.2515	-48.5150	-62.6468	-50.0396	-16.3391	24.1932	54.9296	63.7668
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
39.7504	-1.8382	-41.5896	-63.1917	-59.4876	-29.4826	12.6003	49.4918
58.7400	25.1083	-18.0617	-54.2500	-66.9095	-51.6159	-15.1277	27.3705
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
65.3777	64.5113	35.1631	-8.5376	-48.4109	-68.1412	-60.0694	-27.9643
54.2384	69.3609	55.6404	18.7757	-25.8578	-59.8850	-69.6673	-51.7492
32.5657	63.1902	67.3054	43.1696	0.9109	-41.9890	-68.1936	-67.5786

**Figure 6.15. Two rows of the original feature of the fingerprint replaced by zero rows**

-13.2515	-48.5150	-62.6468	-50.0396	-16.3391	24.1932	54.9296	63.7668
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
39.7504	-1.8382	-41.5896	-63.1917	-59.4876	-29.4826	12.6003	49.4918
58.7400	25.1083	-18.0617	-54.2500	-66.9095	-51.6159	-15.1277	27.3705
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
65.3777	64.5113	35.1631	-8.5376	-48.4109	-68.1412	-60.0694	-27.9643
54.2384	69.3609	55.6404	18.7757	-25.8578	-59.8850	-69.6673	-51.7492
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

**Figure 6.16. Three rows of the original feature of the fingerprint replaced by zero rows**

-13.2515	0.0000	-62.6468	-50.0396	-16.3391	24.1932	54.9296	63.7668
14.1556	0.0000	-57.4675	-62.1471	-40.5157	-1.9108	37.4970	62.6071
39.7504	0.0000	-41.5896	-63.1917	-59.4876	-29.4826	12.6003	49.4918
58.7400	0.0000	-18.0617	-54.2500	-66.9095	-51.6159	-15.1277	27.3705
67.7559	0.0000	9.0100	-34.3391	-62.9618	-65.2899	-40.8292	-0.0031
65.3777	0.0000	35.1631	-8.5376	-48.4109	-68.1412	-60.0694	-27.9643
54.2384	0.0000	55.6404	18.7757	-25.8578	-59.8850	-69.6673	-51.7492
32.5657	0.0000	67.3054	43.1696	0.9109	-41.9890	-68.1936	-67.5786

**Figure 6.17. One column of the original feature of the fingerprint replaced by zero row**

-13.2515	0.0000	-62.6468	-50.0396	0.0000	24.1932	54.9296	63.7668
14.1556	0.0000	-57.4675	-62.1471	0.0000	-1.9108	37.4970	62.6071
39.7504	0.0000	-41.5896	-63.1917	0.0000	-29.4826	12.6003	49.4918
58.7400	0.0000	-18.0617	-54.2500	0.0000	-51.6159	-15.1277	27.3705
67.7559	0.0000	9.0100	-34.3391	0.0000	-65.2899	-40.8292	-0.0031
65.3777	0.0000	35.1631	-8.5376	0.0000	-68.1412	-60.0694	-27.9643
54.2384	0.0000	55.6404	18.7757	0.0000	-59.8850	-69.6673	-51.7492
32.5657	0.0000	67.3054	43.1696	0.0000	-41.9890	-68.1936	-67.5786

**Figure 6.18. Two columns of the original feature of the fingerprint replaced by zero rows**

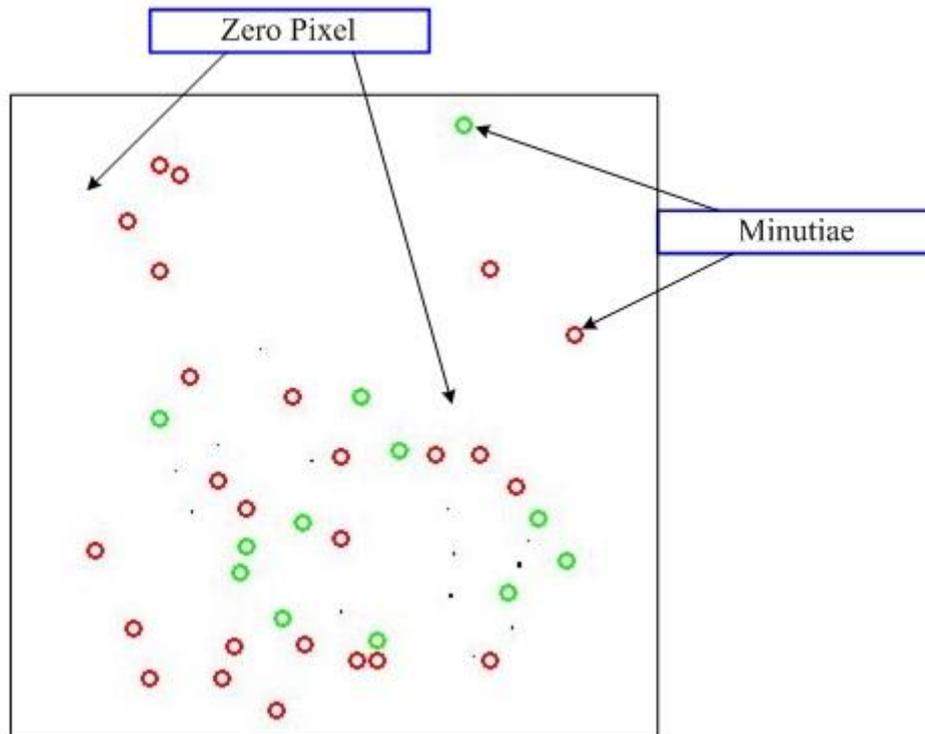
-13.2515	0.0000	-62.6468	-50.0396	0.0000	24.1932	54.9296	0.0000
14.1556	0.0000	-57.4675	-62.1471	0.0000	-1.9108	37.4970	0.0000
39.7504	0.0000	-41.5896	-63.1917	0.0000	-29.4826	12.6003	0.0000
58.7400	0.0000	-18.0617	-54.2500	0.0000	-51.6159	-15.1277	0.0000
67.7559	0.0000	9.0100	-34.3391	0.0000	-65.2899	-40.8292	0.0000
65.3777	0.0000	35.1631	-8.5376	0.0000	-68.1412	-60.0694	0.0000
54.2384	0.0000	55.6404	18.7757	0.0000	-59.8850	-69.6673	0.0000
32.5657	0.0000	67.3054	43.1696	0.0000	-41.9890	-68.1936	0.0000

**Figure 6.19. Three columns of the original feature of the fingerprint replaced by zero rows**

-13.2515	0.0000	-62.6468	-50.0396	0.0000	24.1932	54.9296	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
39.7504	0.0000	-41.5896	-63.1917	0.0000	-29.4826	12.6003	0.0000
58.7400	0.0000	-18.0617	-54.2500	0.0000	-51.6159	-15.1277	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
65.3777	0.0000	35.1631	-8.5376	0.0000	-68.1412	-60.0694	0.0000
54.2384	0.0000	55.6404	18.7757	0.0000	-59.8850	-69.6673	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

**Figure 6.20. Illustrating the combination of the zero row and column of the image**

The ERO operations initially produces no difference in the appearance of the cancellable template, the speed of the general process, and the matching performance of the process. All of the results are identical to the results discussed in the previous section. For example, the unchanged look of the cancellable template occurs because the minutiae are the feature used to generate the cancellable template. Figure 6.21 illustrates how the augmenting process of the zero rows/columns does not affect the appearance of the cancellable template.



**Figure 6.21. The unchanged appearance of the fingerprint features after the augmenting process of the zero row and column in the image**

## 6.5. Discussion

In this chapter, for the FVC2002 and FVC2004 databases, the performance for one fingerprint is examined against seven variants of itself and 72 variants from the other fingerprints. Meanwhile, for the BRC database, the evaluation of one fingerprint is completed against five variants of itself and 54 variants from the others. This research exploits 820 types of fingerprint. Thus, based on the previous results, several observations can be highlighted as follows.

The performance of a biometric system cannot be separated from the authentication stage. This stage becomes important because it aims to check the authenticity of a fingerprint.

Therefore, the system can decide which input of the fingerprint should be either accepted (genuine) or rejected (impostor). However, it has become commonplace in the authentication step that not all the accepted or rejected fingerprints are true genuine cases and true impostors. These conditions are known as false genuines and false impostors. A false genuine and impostor would create a problem if the corresponding rates (EERs) are very large. Hence, the fingerprint with the lowest EER has a chance of becoming a better fingerprint in the database. However, the EER is not the only requirement to acknowledge which fingerprint has a superior error rate. In this research, the threshold value is also determined as a parameter to understand which fingerprint in the same database has the lowest error rate. The reason for this is because the cut off value would show an exemption level for the authentication system to decide on the authenticity of the fingerprint.

Finding an error rate for each fingerprint in the database is required to discover the characteristics of the database when the proposed algorithm is applied. Tables 6.1 - 6.8 show that the lowest level error rate for the FVC2002 and FVC2004 databases is 0.063. Meanwhile, the highest EER and the threshold of each EER could be dissimilar. In terms of the threshold score, the highest score would represent the better condition of the fingerprint. If a fingerprint has a high cut off score, it means that the enquiry fingerprint would be recognized by the system as an authorized fingerprint even with a high qualification matching score. However, the cut off rate does not become a priority in deciding which fingerprint has a better error rate; however, the EER with the lowest score does. For example, in the FVC2002DB2 database, fingerprint 4 has an improved error rate with an EER score of 0.063 and a 0.475 cut off score; compared with the other fingerprints. Notwithstanding this, fingerprint 108 has the highest threshold score of 0.525. Similarly, fingerprint 107 in the FVC2002DB3 database has a better error rate with an EER score of 0.063 and a threshold

score of 0.375. However, fingerprint 108 has a threshold score of 0.525 which is 40% higher than that of fingerprint 107.

Obviously, the FVC2002 (DB1, DB2, DB3, DB4), FVC2004 (DB1, DB2, DB3, DB4), and BRC (DB1Test, DB1Training, DB2) databases use different scanners to obtain fingerprint images. Based on the EER score, the threshold score, and the type of scanner used to acquire the fingerprint, it is apparent that the clarity of the input of fingerprints plays an important role in minimizing the error rate. In other words, the quality of the fingerprint influences how many fingerprints would be classified as genuine owners or impostors and how minimal the error rate is. For example, the highest threshold score for FVC2002DB1; DB2; DB3; DB4, FVC2004DB1; DB2; DB3; DB4, BRCDB1Test; Training and DB2 databases are 0.475, 0.525, 0.525, 0.425, 0.525, 0.175, 0.275, 0.375, 0.825, 0.625, and 0.825 respectively. Referring to these scores, it can be seen that the scores for the BRC databases are better than the other databases since their fingerprints are better image quality.

In order to evaluate the time taken in executing the algorithm, this research offers two possible types of input for the fingerprint. The first type is through using the original fingerprint as an input, while the second type is by selecting a particular area of the original fingerprint to reduce any unneeded features captured by the algorithm process. The latter type requires an additional step, specifically the RoI selection process, to select a desired area of the fingerprint. It is obvious that an extra step would require additional time to complete the algorithm. However, in this research, the size of the input of the fingerprint plays an important role in reducing the time consumed. For example, Tables 6.12 - 6.14 compare the two types of fingerprints. The additional step of the process does not affect the total time taken for execution. In Table 6.15, it is clearly seen that the reduction in size results in less time taken except for the BRCDB1 Training database. The latter case occurred because the

size difference between the original input and the RoI input is only 0.25%, and therefore, the time required for the RoI input is 1.04% more than the original input.

Furthermore, the discussion with regards to some of the prerequisite for the matrices operations should not be a part of these two following cases, such as the size of the arbitrary matrix that is used in the KP operation; and the number and placing of the zero rows or columns on the fingerprint matrix in the ERO operation. In relation to the former one, it should not be a part of the time needed either if the size of the arbitrary matrix is large or small. Figure 6.12 clearly shows that the time consumed by the process would increase when the size of the arbitrary matrix is enlarged. However, at the point at which the size of the matrix is 3 x 3; the taken time is reduce slightly by approximately 3.68% for the FVC2002, 0.0339% for the FVC2004, and 1.54% for the BRC databases. Meanwhile, Figures 6.13 to 6.20 illustrate the zero rows and columns, and the replaced rows and columns of the feature of the fingerprint. Initially, these procedures do not have an impact on the results at all. The appearance of the template of the cancellable fingerprint is still the same as in the figures shown in the two previous chapters, as long as the numbers of zero rows or columns are not more than a third of the size of the rows/columns of the original matrix. Likewise, the speed and matching performance of the process are no different.

## 6.6. Summary

The aim of this chapter has been to evaluate the performance of the proposals discussed in the two previous chapters. Hence, three kinds of evaluation of error rates, time taken and matrices operations requirements are performed to check the performance with the eleven different databases of the fingerprint. One of the evaluations shows that each database

has its own characteristics depending on the type of fingerprint acquired from the database scanner. If the fingerprint scanner produces a fingerprint with a good qualification, the error rate and the threshold of the database can be reliable.

Furthermore, the time consumed by the execution process depends on the size of the input of the fingerprint. The time taken would be reduced if the size is smaller. Subsequently, for a small input fingerprint, even though the RoI step would be added to the algorithm, the total time used for the process would not significantly change with the proviso that the size reduction of the input is not too slight.

Meanwhile, regarding the implementation of the matrices operations, this procedure does not change the results for or the characteristics of the cancellable template, as long as the requirements of the matrices operations are not excessive.

# Chapter 7

## 7. Conclusion and Future Work

This chapter summarises the main aspects of the research work undertaken in generating the template for a cancellable fingerprint. The main contributions planned and targeted in Chapter 1 have been completed and are summarized. Nonetheless, there is still additional research that needs to be conducted in the future. Hence, recommendations are made as guidance to implementing this approach with other applications and to increase the efficiency and quality of the cancellable template. Overall, however, the work described in this thesis has satisfied the aims and objectives mentioned in Chapter 1.

### 7.1. Conclusion

Establishing a cancellable template for a biometric technology such as fingerprint technology is a considerable challenge, especially related to the reissuing ability, multi-application implementation and dependability. The implementation of several matrix operations and requirements for several fingerprint algorithms becomes a continuous work to complete these three important issues. Matrix applications such as the KP operation, ERO operation and Inverse operation can be used as a solution to solve the first two issues. Meanwhile, a sequence of steps of fingerprint enhancement, core-point identification, region of interest, fingerprint classification, and minutiae extraction processes can be utilized to resolve the third issue. In Chapter 1, these issues have been discussed as a challenge to be

taken on and overcome. As documented in this thesis, the aims and objectives have been fulfilled by the present research.

A novel approach is proposed to produce a cancellable fingerprint template exploiting several matrices operations. The KP, ERO and Inverse operations are implemented in the algorithm to obtain a reliable cancellable template. This new idea is based on the principle of achieving a non-invertible matrix. A matrix cannot be inverted as long as the matrix possesses certain criteria, having at least one zero row/column, having a non-square form, and having a row that is a multiple of another row.

The three matrix operations need an appropriate procedure in order to satisfy these three requirements. The KP operation is a procedure used to enlarge the size of an input by taking the tensor product of it with an arbitrary matrix, which will then change the value of each pixel of the original input. This procedure can disguise the appearance of the fingerprint since the original element of the fingerprint has been replaced. ERO provides a procedure to perform several matrix operations, such as rotating, conversing, multiplying and changing each element of the matrix. Meanwhile, the inverse operation could transform a matrix into one with a different value. Three different orders of matrix operations have been introduced to analyze which can provide an improved method to produce a high-quality cancellable template, which are Inverse-KP-ERO procedure; KP-Inverse-ERO procedure; and Inverse-KP procedure. Based on the research results, the first procedure is more secure in terms of protecting the template to be inverted, so as to find the original source of the fingerprint.

In terms of producing a dependable cancellable template, several fingerprint processing steps are implemented by exploiting eleven different databases of fingerprints, FVC2002DB1; DB2; DB3; DB4, FVC2004DB1; DB2; DB3; DB4, BRCDB1Test; Training; DB2. The first process is fingerprint enhancement. This is needed so as to produce a clear

input for all fingerprint processes. For example, an enhanced image of a fingerprint is very helpful in identifying the correct core-point and avoiding a false core-point detection and false minutiae extraction. Moreover, a noise-free input fingerprint is useful in avoiding carrying over unimportant pixels into the cancellable fingerprint template. In this research, the core-point detection approach is appropriate not only for one type of database, but can also be implemented with different types of databases. This improvement is achieved if the input is an enhanced image. Otherwise, if a poor quality image becomes the input, the proposed approach detects a false core-point. Given that the core-point is also utilized in the RoI and fingerprint classification steps, this result has an impact in yielding a progressive result.

A novel approach is proposed to select a particular area in the RoI step to accommodate the needs of a square input form for a cancellable fingerprint and the need to omit unimportant areas for the minutiae extraction step. Even though the RoI stage reduces the area of the fingerprint; this step is required to discard noise evident in the fingerprint image. In the classification of the fingerprint image, there are three requirements: the core point and its number, ridge frequency, and ridge direction; whilst the TA is only an additional requirement. In this thesis, for the FVC2002 database, only 51.25% out of 320 fingerprint images are classified. The false classifications happen because the fingerprints do not meet some of the required criteria.

Finally, a short ridge-line after the core and false-core identification can lead to false classifications in all classes. For likely left/right loop classes especially, this decision is based on the core position and upper- and lower-ridge furrow form and direction. Furthermore, for FVC2004, the percentage of classified fingerprints is slightly higher than for FVC2002. This is because the fingerprint input size in FVC2004 is bigger, so that fingerprint details like the core and TA are better covered than in FVC2002. Nevertheless, as the acquisition quality of

FVC2004 is lower, so then the percentage of false classifications in FVC2004 is higher than in FVC2002. Meanwhile, in the BRC DBI-Test case, as the size of the fingerprints are smaller than in the two previous databases detailed information to classify the fingerprint core, TA and enough ridge length after the core is not provided. This causes the percentages of false classifications and unclassified fingerprints to be higher than with the two other databases.

The performance for one fingerprint from databases FVC2002 and FVC2004 was examined against seven variants of itself and 72 variants from other fingerprints. This means that eighty fingerprints were assessed in total. One is used in the database as an authorized fingerprint. Meanwhile, for the BRC database, the evaluation of one fingerprint was performed against five variants of itself and 54 variants from the others. Thus, this research exploits 820 types of fingerprints.

In this thesis, the performance of a biometric system cannot be considered separately from the authentication stage. This stage is important because it checks the authenticity of a fingerprint. Subsequently, the system can decide which input of a fingerprint should be either accepted (genuine) or rejected (impostor). However, it has become commonplace during authentication that not all the accepted or rejected fingerprints are true genuines and true impostors. These conditions are known as false genuines and false impostors, which create a problem if their rates (EER) are very high. Hence, the fingerprint with the lowest EER has a chance of becoming a better fingerprint in the database. However, the EER is not the only requirement in acknowledging which fingerprint has a better error rate.

In this research, the cut-off point value is also determined as a parameter to recognize which fingerprint in the same database has the lowest error rate. This is because the cut-off point value shows an exemption for the authentication system to decide the authenticity of the

fingerprint. Finding an error rate for each fingerprint in the database is required to discover the characteristics of the database after the proposed algorithm is applied to it. Based on the experiment conducted, the lowest error rate level for databases FVC2002 and FVC2004 is 0.063. Meanwhile, the highest EER and the cut off value for each EER could be dissimilar.

In terms of the cut-off point score, the highest score would represent the better condition of the fingerprint. If a fingerprint has a high cut-off point, it means that the enquiry fingerprint would be recognized by the system as an authorized fingerprint, even with a high qualification matching score. However, the threshold rate does not become a priority in deciding which fingerprint has a better error rate; however, the EER with the lowest score does. Obviously, databases FVC2002 (DB1, DB2, DB3, DB4), FVC2004 (DB1, DB2, DB3, DB4), and BRC (DB1Test, DB1Training, DB2) use different scanners to obtain the fingerprint images. Based on the EER score, the cut-off point score, and the type of scanner used to acquire the fingerprint, it is obvious that the clarity of the input of a fingerprint plays an important role in minimising the error rate. In other words, the quality of fingerprints influences how many would be classified as belonging to an impostor and how minimal the error rate is.

In terms of evaluating the time taken to execute the algorithm, this research has undertaken the evaluation by offering two possible types of input for the fingerprint. The first is the use of the original fingerprint as an input, and the second involves selecting a particular area of the original fingerprint to remove any unneeded features captured during the algorithm process. The latter type requires an additional step, namely the RoI selection process, to select a desired area of the fingerprint.

It is obvious that an extra step would require additional time taken to complete the algorithm. However, in this research, the size of the input of the fingerprint plays an

important role in reducing the length of time that it takes. In fact, the additional step of this process does not affect the total time taken for execution, except for database BRADB1 Training. Furthermore, the time consuming by the process would increase when the size of the arbitrary matrix is enlarged as well. Meanwhile, initially, the zero rows/columns procedures do not have an impact on the cancellable results at all. The cancellable fingerprint template still appears the same as long as the numbers of zero rows or columns are no more than a third of the size of the rows/columns of the original matrix. Similarly, the speed and matching performances of the process are no different.

To conclude, this thesis has presented an alternative approach to producing a cancellable template of a fingerprint. Several supporting requirements are also introduced to standardize the procedure, in order to complete this new cancellable approach. This approach has an advantage which is not possessed by other cancellable algorithms in that it can be implemented with other biometric technologies. Furthermore, the comparison among all databases shows that the BRC databases show better qualification in term of error rates and the cut off level.

## 7.2. Recommendations for Future Work

Based on the research presented in this thesis, there are other possibilities for further research investigation, which should be initiated as follows.

- A challenge for future work will be to implement all of the proposed algorithms and procedures into a different biometric technology. However, it is obvious that other biometric technologies will need different procedures during execution, which will need to be carefully specified.

- In this thesis, the RoI procedures are required because the cancellable algorithm needs a square image. In addition, it is unavoidable that this procedure removes a fraction of the original fingerprint. This means that some information related to the feature of the fingerprint is lost. Therefore, in future work, acquiring a square shape without diminishing the whole surface of the fingerprint needs to be considered by selecting and adjusting the RoI input, rather than by decreasing area of the original image.
- The proposed RoI procedure assigns the core-point as a reference point to select the desired region of the fingerprint. The procedure does not position the core at the centre of the selection area, based on the fact that no fingerprint in any database has its core-point precisely at the centre of the fingerprint. Therefore, in the future work, it is quite important to position the core in the middle of the RoI, and thus the selected RoI would cover the entire surface of the fingerprint.

# References

- [1] A. Ross, S. Dass, and A.K. Jain, “A Deformable Model for Fingerprint Matching,” *Journal of Pattern Recognition, Elsevier*, vol. 38, no. 1, pp. 95-113, Jan. 2005.
- [2] T. Matsumoto, H. Matsumoto, K. Yamada, and S. Hoshino, “Impact of Artificial Gummy Fingers on Fingerprint Systems”, In *Proc. of SPIE, Optical Security and Counterfeit Deterrence Technique IV*, vol. 4677, pp. 275-289, Feb. 2002.
- [3] A.K. Jain, A. Ross, and S. Pankanti, “Biometric: A Tool for Information Security”, *IEEE Trans. Information Forensics and Security*, vol. 1, no. 2, pp. 125-144, Jun. 2006.
- [4] J. K. Schneider, “Ultrasonic Fingerprint Sensors”, *Advances in Biometrics*, Springer, pp. 63-74, 2008.
- [5] H. C. A. van Tilbong and S. Jajodia, “Encyclopedia of Cryptography and Security”, Second Edition, Springer Reference, p. 463, 2011.
- [6] R. Cappelli, D. Maio, D. Maltoni, J. L. Wayman, and A.K. Jain, “Performance Evaluation of fingerprint Verification Systems,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 1, pp. 3-18, Jan. 2006.
- [7] A.K. Jain, L. Hong, and R. Bolle, “On-Line Fingerprint Verification,” *IEEE Transactions on Pattern Recognition and Machines Intelligence*, vol. 19, no. 4, pp. 302-314, Aug, 1996.

- [8] L. Hong and A.K. Jain, "Integrating Faces and Fingerprints for Personal Identification," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 20, no. 12, pp. 1295-1307, Dec. 1998.
- [9] A.K. Jain, A. Ross, and S. Prabhakar, "An Introduction to Biometric Recognition," *IEEE Trans. Circuits Syst. Video Technology, Special Issue Image- and Video-Based Biomet.*, vol. 14, no. 1, pp. 4-20, Jan. 2004.
- [10] S. Prabhakar, S. Pankanti, and A.K. Jain, "Biometric Recognition: Security and Privacy Concerns," *IEEE Security Privacy*, vol. 1, no. 2, pp. 33-42, 2003.
- [11] N. Ratha, J.H. Connell, and R.M. Bolle, "An Analysis of Minutiae Matching Strength," In *Proc. Int. Conf. Audio- Video- Based Biometric Person Authentication*, pp. 223-228, Halmstad, Sweden, 2001.
- [12] U. Uludag, S. Pankanti, S. Prabhakar, A.K. Jain, "Biometric Cryptosystems: Issues and Challenges," in *Proc. of The IEEE*, Vol. 92, No. 6, pp. 948-960, June 2004.
- [13] C. Vielhauer, R. Steinmetz, "Handwriting: Feature Correlation Analysis for Biometric Hashes," *EURASIP Journal on Applied Signal Processing*, Vol. 4, pp. 542-558, 2004.
- [14] N. Ratha, J. Connel, and R. Bolle, "Enhancing Security and Privacy in Biometric-Based Authentication System," *IBM Systems Journal*, vol. 40, no. 3, pp. 614-634, 2001.
- [15] R.M. Bolle, J.H. Connell, and N.K. Ratha, "Biometric perils and Patches," *Pattern Recognition*, vol. 35, no. 12, pp. 2727-2738, 2002.
- [16] B. Schneier, "Biometrics: Uses and Abuses," *Communications of the ACM*, vol. 42, no. 8, page 1, 1999.
- [17] D. Maltoni, D. Maio, A.K. Jain, and S. Prabhakar, "Handbook of Fingerprint Recognition," *New York: Springer-Verlag*, 2003.

- [18] T. Boulton, "Robust Distance Measures for Face-Recognition Supporting Revocable Biometric Token," In *Proc. 7<sup>th</sup> Int. Conf. Autom. Face and Gesture Recog.*, pp. 560-566, Southampton, U.K., Apr. 10-12, 2006.
- [19] A. Ross and R. Govindarajan, "Feature Level Fusion Using Hand and Face Biometrics," In *Proc. Of SPIE Conf. Biometric Technology for Human Identification II*, pp. 196-204, Mar. 2005.
- [20] S.Z. Li and A.K. Jain, Eds., "Handbook of Face Recognition," New York: Springer Verlag, 2004.
- [21] F. Cardinaux, C. Sanderson, and S. Bengio, "User Authentication via Adapted Statistical Models of Face Images," *IEEE Transaction on Signal Processing*, vol. 54, no. 1, pp. 361-373, Jan. 2006.
- [22] P. Campisi, E. Maiorana, and A. Neri, "On-line Signature Based Authentication: Template Security Issues and Countermeasures," In *N.V. Boulgouris, K.N. Plataniotis, & E. Micheli-Tzanakou (Eds.), Biometrics: Theory, Methods, and Applications. Wiley/IEEE*, 2008.
- [23] D. Bhattacharyya, S.K. Bandopadhyaya, P. Das, D. Ganguly, and S. Mukherjee, "Statistical Approach for Offline Handwritten Signature Verification," *Journal of Computer Science, Science Publication*, vol. 4, no. 3, pp. 181-185, May. 2008.
- [24] S. Kanade, D. Petrovska-Delacretaz, and B. Dorizzi, "Cancellable Iris Biometrics and Using Error Correcting Codes to Reduce Variability in Biometric Data," In *Proc. of IEEE Conference on Computer Vision and Pattern Recognition(CVPR)*, pp. 120-127, 2009.
- [25] S.R. Ganorkar, A.A. Ghatol, "Iris Recognition: An Emerging Biometric Technology," In *Proc. Of the 6<sup>th</sup> WSEAS International Conference on Signal Processing, Robotics and Automation*, pp. 91-96, Greece, Feb. 2007.

- [26] J.L. Wayman, A.K. Jain, D. Maltoni, and D. Maio, Eds., "Biometric Systems: Technology, Design and Performance Evaluation," New York: Springer Verlag, 2005.
- [27] J.G. Daugman, "The Importance of Being Random: Statistical Principles of Iris Recognition," *Journal of Pattern Recognition, Elsevier*, vol. 36, no. 2, pp. 279-291, Feb. 2003.
- [28] W. Xu and M. Cheng, "Cancellable Voiceprint Template Based on Chaff-Points-Mixture Method," In *Proc. of International Conference on Computational Intelligence and Security*, pp. 263-266, 2008.
- [29] S. Furui, "Recent Advances in Speaker Recognition," In *Proc. of International Conference on Audio and Video Based Biometric Person Authentication*, pp. 859-872, UK, Mar. 1997.
- [30] N.K. Ratha, S. Chikkerur, J.H. Connell, and R.M. Bolle, "Generating Cancellable Fingerprint Templates," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 29, no. 4, pp. 561-572, 2007.
- [31] A. Nagar and A.K. Jain, "On the Security on Non-Invertible Fingerprint Template Transformed," *IEEE Workshop on Information Forensics and Security (WIFS)*, London, Dec. 2009.
- [32] C. Lee and J. Kim, "Cancellable Fingerprint Templates using Minutiae-Based Bit-Strings," *J Network Comp. Appl.*, 2010, doi:10.1016/j.jnca.2009.12.011.
- [33] C. Lee, J. Choi, K. Toh, S. Lee, and J. Kim, "Alignment-Free Cancellable Fingerprint Templates Based on Local Minutiae Information," *IEEE Trans. on Systems Man. And Cybernetics-B*, vol. 37, pp. 980-992, 2007.
- [34] F. Farooq, R.M. Bolle, T.Y. Jea, and N. Ratha, "Anonymous and Revocable Fingerprint Recognition," In *Proc. Computer Vision and Pattern Recognition*, Minneapolis, June, 2007.

- [35] S. Chikkerur, N.K. Ratha, H. Connell, and R.M. Bolle, "Generating Registration-Free Cancellable Fingerprint Templates," In *BTAS08*, pp. 1-6, 2008.
- [36] J. Bringer, H. Chabanne, B. Kindarji, "The Best of Both Worlds: Applying Secure Sketches to Cancellable Biometrics," *Science of Computer Programming*, vol. 74, no. 1-2, pp. 43-51, 2008.
- [37] B. Yang, C. Busch, M. Derawi, P. Bours, and D. Gafurov, "Geometric-Aligned Cancellable Fingerprint Templates," In *Proc. of the 15<sup>th</sup> Int. Conf. on Image Analysis and Processing, LNCS*, Vol. 5716, pp. 490-499, Vietrisul Mare, Italy, Sept. 08-11, 2009.
- [38] F. Quan, S. Fei, C. Anni, and Z. Feifei, "Cracking Cancellable Fingerprint Template of Ratha," In *International Symposium on Computer Science and Computational Technology (ISCSCT '08)*, vol. 2, pp. 572-575, 2008.
- [39] S.W. Shin, M.-K. Lee, D.S. Moon, and K.Y. Moon, "Dictionary Attack on Functional Transform-Based Cancellable Fingerprint Templates," *ETRI Journal*, vol. 31, no. 5, pp. 628-630, 2009.
- [40] S. Tulyakov, F. Farooq, and V. Govindaraju, "Symmetric Hash Functions for Fingerprint Minutiae," In *International Workshop on Pattern Recognition for Crime Prevention, Security, and Surveillance (ICAPR '05)*, vol. 3687, pp. 30-38, 2005.
- [41] R. Ang, R. Safavi-Naini, and L. Mc. Aven, "Cancellable Key-Based Fingerprint Templates," In *Proc. of Information Security and Privacy: 10<sup>th</sup> Australasian Conference (ACISP '05)*, pp. 242-252, 2005.
- [42] A.T.B. Jin and L.M. Hui, "Cancellable Biometrics," *Scholarpedia*, vol. 5, no. 1, page 9201, 2010. doi: 10.4249/scholarpedia.9201.
- [43] M. Kuhn, R. Anderson, J. Daugman, "Tamper Resistance: A Cautionary Note," *Workshop on Electronic Commerce*. 1996.

- [44] H. Anton, C. Rorres, “Elementary Linear Algebra, Application Version: Ninth Edition,” *Wiley eGrade*, 2005.
- [45] A.J. Laub, “Matrix Analysis for Scientists and Engineers,” *The Society for Industrial and Applied Mathematics*, pp. 139-142, 2005.
- [46] H. Fronthaler, K. Kollreider, and J. Bigun, “Local Features for Enhancement and Minutiae Extraction in Fingerprints”, *IEEE Transaction on Image Processing*, vol. 17, no. 3, pp. 354-363, March. 2008.
- [47] L. Hong, Y. Wan, and A.K. Jain, “Fingerprint Image Enhancement: Algorithm and Performance Evaluation”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, no. 8, pp. 777-789, 1998.
- [48] S. Prabhakar, A.K. Jain, J. Wang, S. Pankanti, and R. Bolle, “Minutiae Verification and Classification for Fingerprint Matching”, In *Proceeding of 15<sup>th</sup> International Conference Pattern Recognition (ICPR)*, vol. 1, pp. 25-29, September 2000.
- [49] A. Ross, A.K. Jain, and J. Reisman, “A Hybrid Fingerprint Matcher”, *Pattern Recognition*, vol. 36, no. 11, pp. 1657-1672, 1995.
- [50] A.K. Jain, S. Prabhakar, and L. Hong, “A Multichannel Approach to Fingerprint Classification”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 21, no. 4, pp. 348-359, 1999.
- [51] J.G Daugman, “Uncertainty Relation for Resolution in Space, Spatial Frequency, and Orientation Optimized by Two-Dimensional Visual Cortical Filters”, In *Journal of the Optical Society of America (A)*, vol. 2, no. 7, pp. 1160-1169, July 1985.
- [52] D.B.G. Sherlock, D.M. Monro, and K. Millard, “Fingerprint Enhancement by Directional Fourier Filtering”, In *IEE Proc. Vis. Image Signal Processing*, vol. 141, pp. 87-94, 1994.

- [53] N.K. Ratha, S. Chen, and A.K. Jain, "Adaptive Flow Orientation-Based Feature Extraction in Fingerprint Images", *Pattern Recognition*, vol. 28, no. 11, pp. 1657-1672, 1995.
- [54] A.M. Basen and S.H. Gerez, "Systematic Methods for the Computation of the Directional Fields and Singular Points of Fingerprints", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 905-919, 2002.
- [55] M. Kass and A. Witkin, "Analyzing Oriented Patterns", *Computer Vision, Graphics, and Image Processing*, vol. 37, no. 3, pp. 362-385, 1987.
- [56] J. Bigun and G.H. Granlund, "Optimal Orientation Detection of Linear Symmetry", In *Proc. First International Conference on Computer Vision*, pp. 433-438, 1987.
- [57] R.C. Gonzalez and R.E. Woods, "Digital Image Processing (Third Edition)", Prentice Hall, 2007.
- [58] L. O’Gorman and J.V. Nickerson, "An Approach to Fingerprint Filter Design", *Pattern Recognition*, vol. 22, no. 1, pp. 29-38, 1989.
- [59] M. Liu, X. Jian, and A.C. Kot, "Fingerprint Reference-Point Detection", *EURASIP Journal on Advances in Signal Processing*, vol. 2005, no. 4, pp. 498-509, 2005.
- [60] M.A. Oliveira and N.J. Leite, "A Multiscale Directional Operator and Morphological Tools for Reconnecting Broken Ridges in Fingerprint Images", *Pattern Recognition*, vol. 41, no. 1, pp. 367-377, 2008.
- [61] P. Lo, "Method and Apparatus for Adaptive Hierarchical Processing of Print Images", US Patent Application Publication No. 2007/0292005A1, 2007.
- [62] T. Kamei and M. Mizoguchi, "Image Filter Design for Fingerprint Enhancement", In *Proceeding of International Symposium on Computer Vision*, pp. 109-114, November, 1995.

- [63] S.C. Dass, “Markov Random Field Models for Directional Field and Singularity Extraction in Fingerprint Images”, *IEEE Transactions on Image Processing*, vol. 13, no. 10, pp. 1358-1367, 2004.
- [64] K.C. Lee and S. Prabhakar, “Probabilistic Orientation Field Estimation for Fingerprint Enhancement and Verification”, In *Proc. Biometrics Symposium (BSYM)*, pp. 41-46, September 2008.
- [65] S.Z. Li, “Markov Random Field Modeling in Image Analysis (Third Edition), Springer, 2009.
- [66] A. Blake, P. Kohli, and C. Rother, Eds., “Markov Random Fields for Vision and Image Processing”, MIT Press, 2011.
- [67] J. Gu, J. Zhou, and C. Yang, “Fingerprint Recognition by Combining Global Structure and Local Cues”, *IEEE Transactions on Image Processing*, vol. 15, no. 7, pp. 1952-1964, 2006.
- [68] Y. Wang, J. Hu, and D. Phillips, “A Fingerprint Orientation Model Based on 2D Fourier Expansion (FOMFE) and Its Application to Singular-Point Detection and Fingerprint Indexing”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 4, pp. 573-585, 2007.
- [69] B.G. Sherlock and D.M. Monro, “A Model for Interpreting Fingerprint Topology”, *Pattern Recognition*, vol. 26, no. 7, pp. 1047-1055, 1993.
- [70] J. Zhou and J. Gu, “A Model-Based Method for the Computation of Fingerprints’ Orientation Field”, *IEEE Transactions on Image Processing*, vol. 13, no. 6, pp. 821-835, 2004.
- [71] S. Huckemann, T. Hotz, and A. Munk, “Global Models for the orientation Field of Fingerprints: An Approach Based on Quadratic Differentials”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 30, no. 9, pp. 1507-1519, 2008.

- [72] S. Yoon, J. Feng, and A.K. Jain, "On Latent Fingerprint Enhancement", In *SPIE Biometric Technology for Human Identification VII*, vol. 7667, no. 1, pp. 766-707, 2010.
- [73] A. Julasayvake and S. Choomchuay, "An Algorithm for Fingerprint Core Point Detection", *International Symposium on Signal Processing and Its Applications*, pp. 1-4, 2007.
- [74] N.K. Johal and A. Kamra, "A Novel Method for Fingerprint Core Point Detection", *International Journal of Scientific and Engineering Research*, vol. 2, issue. 4, April, 2011.
- [75] K. Nilsson and J. Bigun, "Localization of Corresponding Points in Fingerprints by Complex Filtering", *Pattern Recognition Letters*, vol. 24, pp. 2135-2144, 2003.
- [76] C.H. Park, J.J. Lee, M.J.T. Smith, S.I. Park, and K.H. Park, "Directional Filter Bank-Based Fingerprint Feature Extraction and Matching", *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 14, no. 1, pp. 74-85, January 2004.
- [77] P. Kapsalas, K. Rapantzikos, A. Sofou, and Y. Avrithis, "Regions of Interest for Accurate Object Detection", in *Proc. Of Sixth International Workshop on Content-Based Multimedia Indexing (CBMI 2008)*, pp.147-154, June 2008.
- [78] F. Galton, "Fingerprints", McMillan, London, 1893.
- [79] E. Henry, "Classification and Uses of Finger Prints", Routledge, London, 1900.
- [80] G.T. Candela, P.J. Grother, C.I. Watson, R.A. Wilkinson, C.L. Wilson, "PCASYS – A Pattern-Level Classification Automation System for Fingerprints", Technique Report, NIST TR 5647, 1995.
- [81] K. Karu and A.K. Jain, "Fingerprint Classification", *Pattern Recognition*, vol. 29, no. 3, pp. 389-404, 1996.

- [82] C.H. Park and H. Park, "Fingerprint Classification using Fast Fourier Transform and Non-Linear Discriminant Analysis", *Pattern Recognition*, vol. 38, no. 4, pp. 495-505, 2005.
- [83] A. Senior, "A Combination Fingerprint Classifier", *IEEE Transaction of Pattern Analysis and Machine Intelligence*, vol. 23, no. 10, pp. 1165-1174, 2001.
- [84] B. Bhanu, X. Tan, "Fingerprint Indexing Based on Novel Features of Minutiae Triplets", *IEEE Transaction of Pattern Analysis and Machine Intelligence*, vol. 25, no. 5, pp. 616-622, 2003.
- [85] X. Tan, B. Bhanu, Y. Lin, "Fingerprint Identification: Classification vs. Indexing", In *Proceedings of IEEE Conference on Advanced Video and Signal Based Surveillance*, pp. 151-156, Miami, Florida, 2003.
- [86] R. Cappelli, D. Maio, D. Maltoni, "Fingerprint Classification Based on Multi-Space KL", In *Proceeding of Workshop on Automatic Identification Advanced Technologies*, pp. 117-120, 1999.
- [87] X. Jiang, M. Liu, A.C. Kot, "Fingerprint Retrieval for Identification", *IEEE Trans. Inf. Forensics Secur.*, vol. 1, no. 4, 532-542, 2006.
- [88] M. Liu, X. Jiang, A.C. Kot, "Efficient Fingerprint Search Based on Database Clustering", *Pattern Recognition*, vol. 40, no. 6, pp. 1793-1803, 2007.
- [89] P. Gother, E. Tabassi, "Performance of Biometric Quality Measures", *IEEE Transaction on Pattern Recognition and Machine Intelligence*, vol. 29, no. 4, pp. 531-543, 2007.
- [90] H. Frontaler, K. Kollreider, J. Bigun, J. Fierrez, F. Alonso-Fernandez, J. Ortega-Garcia, and J. Gonzalez-Rodriguez, "Fingerprint Image Quality Estimation and Its Application to Multi-Algorithm Verification", *IEEE Transaction on Information Forensics and Security*, vol. 3, no.2, pp. 331-338, 2008.

- [91] L. Hong, Y. Wand, A.K. Jain, “Fingerprint Image Enhancement: Algorithm and Performance Evaluation”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, no. 8, pp. 777-789, 1998.
- [92] Y. Chen, S. Dass, A. Jain, “Fingerprint Quality Indices for Predicting Authentication Performance”, In *Audio- and Video-Based Biometric Person Authentication*, p. 160, 2005.
- [93] D. Maio and D. Maltoni, “Direct Gray-Scale Minutiae Detection in Fingerprints”, *IEEE Transactions of Pattern Analysis and Machine Intelligence*, vol. 19, no. 1, pp. 27-40, 1997.
- [94] <http://bias.csr.unibo.it/fvc2002/databases.asp>.
- [95] <http://bias.csr.unibo.it/fvc2004/databases.asp>.
- [96] Biometrics Research Center, Department of Computing, The Hong Kong Polytechnic University, [cszhang@comp.polyu.edu.hk](mailto:cszhang@comp.polyu.edu.hk).
- [97] R. Cappelli, A. Lumini, D. Maio, D. Maltoni, “Fingerprint Classification by Directional Image Partitioning”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 21, no. 5, pp. 402-421, 1999.
- [98] A.K. Jain, S. Prabhakar, L. Hong, and S. Pankanti, “Filterbank-Based Fingerprint Matching”, *IEEE Transaction on Image Processing*, vol. 9, no. 5, pp. 846-859, 2000.
- [99] A.M. Bazen, S.H. Gerez, “An intrinsic Coordinate system for Fingerprint Matching”, In *Third International Conference on Audio- and Video-Based Biometric Person Authentication*, pp. 198-204, Springer Verlag, 2001.
- [100] J.C. Amengual, A. Juan, J.C. Prez, F. Prat, S. Sez, and J.M. Vilar, “Real-Time Minutiae Extraction in Fingerprint Images”, In *Proceeding of the 6<sup>th</sup> International Conference on Image Processing and Its Application*, pp. 871-875, July 1997.

- [101] B.M. Mehtre, "Fingerprint Image Analysis for Automatic Identification", *Machine Vision and Application* 6, vol. 2, pp. 124-139, 1993.
- [102] S. Kasaei, M. Deriche, and B. Boashash, "Fingerprint Feature Extraction using Bloc-Direction on Reconstructed Images", In *IEEE region TEN Conference Digital Signal Processing Applications*, pp. 303-306, December 1997.
- [103] H.A. Tamura, "A Comparison of Line Thinning Algorithms from Digital Geometry Viewpoint", In *Proceeding of the 4<sup>th</sup> International Conference on Pattern Recognition*, pp. 715-719, 1978.
- [104] A. Ross and A. Jain, "Biometric Sensor Interoperability: A Case Study in Fingerprints", *BioAW 2004*, LNCS 3085, pp. 134-145, 2004.
- [105] S. Andrilli, D. Hecker, "Elementary Linear Algebra: Elementary Row Operation", Fourth Edition, Elsevier, pp. 82-94, Canada, 2010.
- [106] S. Andrilli, D. Hecker, "Elementary Linear Algebra: Inverses of Matrices", Fourth Edition, Elsevier, pp. 125-133, Canada, 2010.

# Appendix

## A. 1. Elementary Row Operation

Numerous methods are available for locating a complete solution for a given linear system. The first is Gaussian elimination. This method involves systematically replacing most of the coefficients in the system with simpler numbers (1's and 0's) by using elementary row operations (ERO) to obtain the complete solution.

In the Gaussian elimination procedure, the basic step to undertake is to examine each column of an augmented matrix of the given system from left to right in rotation. Subsequently, if possible, a special entry as a reference entry is chosen and converted to value 1 in each column, and then the entries below the reference are of zero out later. The reference will be changeable from column to column, starting from the row above onto the row below. This means that each new reference entry will occur on a row below. There are three operations that are allowed to be used on the augmented matrix in the Gaussian elimination method i.e.:

- (I) Multiplying a row by a nonzero scalar,
- (II) Adding a scalar multiple of one row to another row,
- (III) Switching the positions of two rows in the matrix.

For example, if the following system of linear equations as follows:

$$\begin{cases} 4x-4y-12z=32 \\ 6x-3y-9z=19; \\ 2x-4y-17z=41 \end{cases} \quad (\text{A.1})$$

Then the augmented matrix of this system is:

$$\left[ \begin{array}{ccc|c} 4 & -4 & -12 & 32 \\ 6 & -3 & -9 & 19 \\ -2 & -4 & -17 & 41 \end{array} \right]; \quad (\text{A.2})$$

The following step is to perform row operations on this matrix to give it a simpler form, proceeding through the columns from left to right. Starting with the first column, choose element matrix (1,1) as the first reference entry and place the value 1 in this position. It is observed that the row containing the current reference entry is currently the reference row. When placing 1 in the matrix, a type (I) operation can be performed to multiply the reference row by the reciprocal of the reference entry. In this case, it is multiplied by 0.25 for each element of the first row:

$$\text{type(I) operation: } (1) \leftarrow \frac{1}{4}(1); \quad (\text{A.3})$$

$$\left[ \begin{array}{ccc|c} \boxed{1} & -1 & -3 & 8 \\ 4 & -2 & -6 & 19 \\ 2 & -4 & -17 & 41 \end{array} \right]; \quad (\text{A.4})$$

Subsequently, all the entries below this first reference entry should be converted to 0. As each entry is changed to 0, it is called the target, and its row is called the target row. To change a target entry to 0, type (II) row operation can be used.

$$(II):(\text{target row})\leftarrow(-\text{target value})\times(\text{reference row})+(\text{target row}); \quad (A.5)$$

For example, to zero out (target) the element (2, 1) entry, the type (II) operation is used as follows:

$$(2) \leftarrow (-6) \times (1) + (2); \quad (A.6)$$

(-4) x (row1)	-6	6	18	-48
(row2)	6	-3	-9	19
(sum)	0	3	9	-29

The resulting sum is now substituted in place of the old row 2, producing a

$$\text{type (II) operation: } (2) \leftarrow (-6) \times (1) + (2); \quad (A.7)$$

$$\left[ \begin{array}{ccc|c} \boxed{1} & -1 & -3 & 8 \\ 0 & 3 & 9 & -29 \\ 2 & -4 & -17 & 41 \end{array} \right]; \quad (A.8)$$

Note that even though row 1 was multiplied by -4 in the side calculation, row 1 itself was not changed in the matrix. Only row 2, the target row, was altered by this type (II) row operation.

Similarly, to target the element (1, 3), that is, to convert it to 0, and thus, row 3 becomes the target now, and another type (II) row operation is used. Row 3 is replaced with (-2) x (row 1) + (row 3). This gives:

$$\text{type (II) operation: } (3) \leftarrow (-2) \times (1) + (3); \tag{A.9}$$

### Side Calculation

(-3) x (row1)	-2	2	6	-16
(row3)	2	-4	-17	41
(sum)	0	-2	-11	25

### Resulting Matrix

$$\left[ \begin{array}{ccc|c} \boxed{1} & -1 & -3 & 8 \\ 0 & 3 & 9 & -29 \\ 0 & -2 & -11 & 25 \end{array} \right]; \tag{A.10}$$

Hence, the row operation for the first column is completed. The next target is for the second column. The reference entry for this column must be beneath the previous reference, so element (2, 2) is chosen as the new reference entry. A type (I) operation is performed on the reference row to convert the reference entry to a value of 1. Multiplying each entry of row 2 by 1/3 (the reciprocal of the reference entry):

type (I) operation:  $(2) \leftarrow \frac{1}{3}(2)$ ; (A.11)

Resulting matrix =  $\left[ \begin{array}{ccc|c} 1 & -1 & -3 & 8 \\ 0 & \boxed{1} & 3 & -\frac{29}{3} \\ 0 & -2 & -11 & 25 \end{array} \right]$ ; (A.12)

A type (II) operation now is used to target the element (3, 2) and row 3.

type (II) operation:  $(3) \leftarrow 2 \times (2) + (3)$ ; (A.13)

**Side Calculation**

(2) x (row2)	0	2	6	-(58/3)
(row3)	0	-2	-11	25
(sum)	0	0	-5	17/3

**Resulting Matrix**

$\left[ \begin{array}{ccc|c} 1 & -1 & -3 & 8 \\ 0 & \boxed{1} & 3 & -29/3 \\ 0 & 0 & 5 & 17/3 \end{array} \right]$ ; (A.14)

The last matrix corresponds to:

$$\begin{cases} x-y-3z=8 \\ y+3z=-\frac{29}{3}, \\ 5z=\frac{15}{3} \end{cases} \quad (\text{A.15})$$

After Gaussian elimination, the columns having no reference entries are often referred to as non-reference columns, while those with pivots are called reference columns. It should be noted that the columns to the left of the augmentation bar correspond to the variables  $x_1$ ,  $x_2$ , and so on, in the system. The variables for the non-reference columns are called independent variables, while those for reference columns are dependent variables. If a given system is consistent, solutions are established by letting each independent variable take on any real value whatsoever. The values of the dependent variables are then calculated from these choices.

These row operations can be concluded as follows [105]. If a row operation  $R$  is performed on a matrix  $A$ , the resulting matrix by  $R(A)$  is represented as:

*Let  $A$  and  $B$  be matrices for which the product  $AB$  is defined.*

*If  $R$  is any row operation,*

*then*

$$R(AB)=(R(A))B \quad (\text{A.16})$$

Meanwhile,

*if*

*$R_1, \dots, R_n$  are row operations,*

*then*

$$R_n \left( \dots \left( R_2 \left( R_1 (AB) \right) \dots \right) \right) = \left( R_n \left( \dots \left( R_2 \left( R_1 (A) \right) \dots \right) \right) \right) B \quad (\text{A.17})$$

Part 1 of this theorem asserts that whenever a row operation is performed on the product of two matrices, the same answer is obtained by performing the row operation on the first matrix alone before multiplying. Part 1 is proved by considering each type of row operation in turn. Part 2 generalizes this result to any finite number of row operations and is proved by using part 1 and induction.

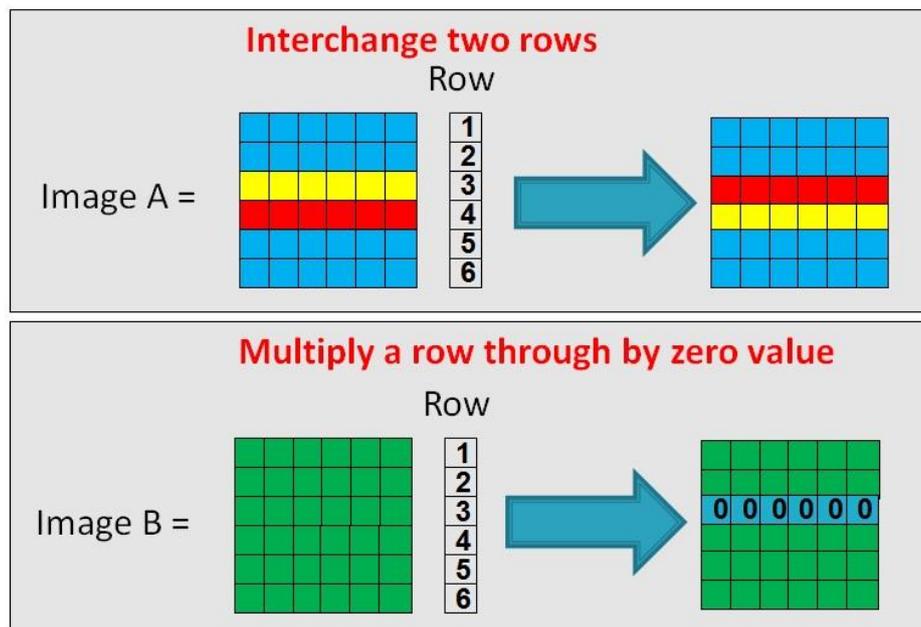


Figure A.1. Illustration of ERO

## A. 2. Kronecker Product

### A.2.1. Definition and Examples

Let  $A \in \mathbb{R}^{m \times n}$ ,  $B \in \mathbb{R}^{p \times q}$ . Then the Kronecker product (or tensor product) of A and B is defined [17] as the matrix:

$$A \otimes B = \begin{bmatrix} a_{11}B & \cdots & a_{1n}B \\ \vdots & \ddots & \vdots \\ a_{m1}B & \cdots & a_{mn}B \end{bmatrix} \in \mathbb{R}^{mp \times nq}; \quad (\text{A.18})$$

Obviously, the same definition holds if  $A$  and  $B$  are complex-valued matrices. For example,

1. Let  $A = \begin{bmatrix} 1 & 2 & 3 \\ 3 & 2 & 1 \end{bmatrix}$  and  $B = \begin{bmatrix} 2 & 1 \\ 2 & 3 \end{bmatrix}$ . Then

$$A \otimes B = \begin{bmatrix} B & 2B & 3B \\ 3B & 2B & B \end{bmatrix} = \begin{bmatrix} 2 & 1 & 4 & 2 & 6 & 3 \\ 2 & 3 & 4 & 6 & 6 & 9 \\ 6 & 3 & 4 & 2 & 2 & 1 \\ 6 & 9 & 4 & 6 & 2 & 3 \end{bmatrix}; \quad (\text{A.19})$$

Note that  $B \otimes A \neq A \otimes B$ .

2. For any  $B \in \mathbb{R}^{p \times q}$ ,

$$I_2 \otimes B = \begin{bmatrix} B & 0 \\ 0 & B \end{bmatrix}; \quad (\text{A.20})$$

Replacing  $I_2$  by  $I_n$  yields a block diagonal matrix with  $n$  copies of  $B$  along the diagonal.

3. Let  $B$  be an arbitrary  $2 \times 2$  matrix. Then:

$$B \otimes I_2 = \begin{bmatrix} b_{11} & 0 & b_{12} & 0 \\ 0 & b_{11} & 0 & b_{12} \\ b_{21} & 0 & b_{22} & 0 \\ 0 & b_{21} & 0 & b_{22} \end{bmatrix}; \quad (\text{A.21})$$

The extension to arbitrary  $B$  and  $I_n$  is obvious.

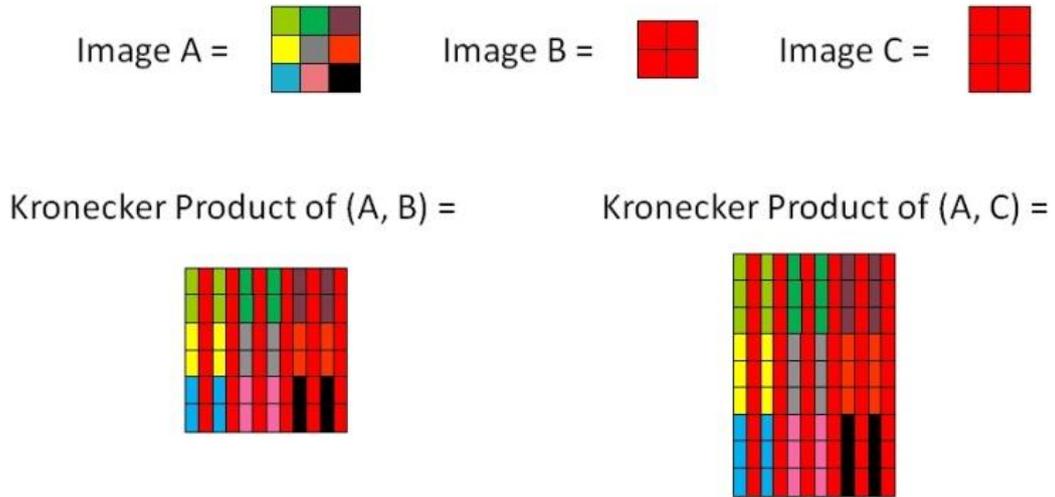


Figure A.2. Illustration of KP operation

4. Let  $x \in \mathbb{R}^m$ ,  $y \in \mathbb{R}^n$ . Then

$$x \otimes y = [x_1 y^T, \dots, x_m y^T]^T = [x_1 y_1, \dots, x_1 y_n, x_2 y_1, \dots, x_m y_n]^T \in \mathbb{R}^{mn}; \quad (\text{A.22})$$

5. Let  $x \in \mathbb{R}^m$ ,  $y \in \mathbb{R}^n$ . Then

$$x \otimes y = [x_1 y, \dots, x_m y]^T = \begin{bmatrix} x_1 y_1 & \cdots & x_1 y_n \\ \vdots & \ddots & \vdots \\ x_m y_1 & \cdots & x_m y_n \end{bmatrix} = xy^T \in \mathbb{R}^{m \times n}; \quad (\text{A.23})$$

### A.2.2. Properties of the Kronecker Product

Let  $A \in \mathbb{R}^{m \times n}$ ,  $B \in \mathbb{R}^{r \times s}$ ,  $C \in \mathbb{R}^{n \times p}$ , and  $D \in \mathbb{R}^{s \times t}$

Then:

$$(A \otimes B)(C \otimes D) = AC \otimes BD \quad (\in \mathbb{R}^{mr \times pt}); \quad (\text{A.24})$$

Simply verify that:

$$\begin{aligned} (A \otimes B)(C \otimes D) &= \begin{bmatrix} a_{11}B & \cdots & a_{1n}B \\ \vdots & \ddots & \vdots \\ a_{m1}B & \cdots & a_{mn}B \end{bmatrix} \begin{bmatrix} c_{11}B & \cdots & c_{1p}B \\ \vdots & \ddots & \vdots \\ c_{n1}B & \cdots & c_{np}B \end{bmatrix} \\ &= \begin{bmatrix} \sum_{k=1}^n a_{1k}c_{k1}BD & \cdots & \sum_{k=1}^n a_{1k}c_{kp}BD \\ \vdots & \ddots & \vdots \\ \sum_{k=1}^n a_{mk}c_{k1}BD & \cdots & \sum_{k=1}^n a_{mk}c_{kp}BD \end{bmatrix} \\ &= AC \otimes BD; \end{aligned} \quad (\text{A.25})$$

where:

1. For all A and B,

$$(A \otimes B)^T = A^T \otimes B^T \quad (\text{A.26})$$

2. If  $A \in \mathbb{R}^{n \times n}$  and  $B \in \mathbb{R}^{m \times m}$  are symmetric, then  $A \otimes B$  is symmetric.

3. If A and B are non-singular,

$$(A \otimes B)^{-1} = A^{-1} \otimes B^{-1}; \quad (\text{A.27})$$

Using property 1, simply note that:

$$(A \otimes B)(A^{-1} \otimes B^{-1}) = I \otimes I = I \quad (\text{A.28})$$

4. If  $A \in \mathbb{R}^{n \times n}$  and  $B \in \mathbb{R}^{m \times m}$  are normal, then  $A \otimes B$  is normal.

Proof:

$$\begin{aligned}
 (A \otimes B)^T (A \otimes B) &= (A^T \otimes B^T) (A \otimes B) \\
 &= A^T A \otimes B^T B \\
 &= A A^T \otimes B B^T \\
 &= (A \otimes B) (A \otimes B)^T; \tag{A.29}
 \end{aligned}$$

5. If  $A \in \mathbb{R}^{n \times n}$  is orthogonal and  $B \in \mathbb{R}^{m \times m}$  is orthogonal, then  $A \otimes B$  is orthogonal.

Example:

$$\text{Let } A = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix} \text{ and } B = \begin{bmatrix} \cos \phi & \sin \phi \\ -\sin \phi & \cos \phi \end{bmatrix} \tag{A.30}$$

Subsequently, it is easily observed that  $A$  is orthogonal with eigenvalues  $e^{\pm j\theta}$  and  $B$  is orthogonal with eigenvalues  $e^{\pm j\phi}$ . Then the  $4 \times 4$  matrix  $A \otimes B$  is also orthogonal with eigenvalues  $e^{\pm j(\theta+\phi)}$  and  $e^{\pm j(\theta-\phi)}$ .

6. Let  $A \in \mathbb{R}^{m \times n}$  have singular value decomposition  $U_A \Sigma_A V_A^T$  and let  $B \in \mathbb{R}^{p \times q}$  have singular value decomposition  $U_B \Sigma_B V_B^T$ . Then  $(U_A \otimes U_B) (\Sigma_A \otimes \Sigma_B) (V_A^T \otimes V_B^T)$  yields a singular value decomposition of  $A \otimes B$  (after a simple reordering of the diagonal elements of  $\Sigma_A \otimes \Sigma_B$  and the corresponding right and left singular vectors).

7. Let  $A \in \mathbb{R}^{m \times n}$  have singular values  $\sigma_1 \geq \dots \geq \sigma_r > 0$ , and

let  $B \in \mathbb{R}^{p \times q}$  have singular values  $\tau_1 \geq \dots \geq \tau_s > 0$ .

Then  $A \otimes B$  (or  $B \otimes A$ ) has  $rs$  singular values  $\sigma_1 \tau_1 \geq \dots \geq \sigma_r \tau_s > 0$  and

$$\text{rank}(A \otimes B) = (\text{rank } A)(\text{rank } B) = \text{rank}(B \otimes A). \quad (\text{A.31})$$

8. Let  $A \in \mathbb{R}^{n \times n}$  have eigenvalues  $\lambda_i, i \in \underline{n}$ , and

let  $B \in \mathbb{R}^{m \times m}$  have eigenvalues  $\mu_j, j \in \underline{m}$ .

Then  $mn$  eigen values of  $A \otimes B$  are  $\lambda_1 \mu_1, \dots, \lambda_1 \mu_m, \lambda_2 \mu_1, \dots, \lambda_2 \mu_m, \dots, \lambda_n \mu_m$  (A.32)

Moreover, if  $x_1, \dots, x_p$  are linearly independent right eigenvectors of  $A$  corresponding to  $\lambda_1, \dots, \lambda_p$  ( $p \leq n$ ) and,

$z_1, \dots, z_q$  are linearly independent right eigenvectors of  $B$  corresponding to  $\mu_1, \dots, \mu_q$  ( $q \leq m$ ),

then  $x_i \otimes z_j \in \mathbb{R}^{mn}$  are linearly independent right eigenvectors of  $A \otimes B$  corresponding to  $\lambda_i \mu_j, i \in \underline{p}, j \in \underline{q}$ .

Proof: the basic idea of the proof is as follows:

$$\begin{aligned} (A \otimes B)(x \otimes z) &= Ax \otimes Bz \\ &= \lambda x \otimes \mu z \\ &= \lambda \mu (x \otimes z) \end{aligned} \quad (\text{A.33})$$

In general, if  $A$  and  $B$  have Jordan form decomposition given by  $P^{-1}AP = J_A$  and  $Q^{-1}BQ = J_B$ , respectively, then the subsequent Jordan-like structure is as follows:

$$\begin{aligned}
(P \otimes Q)^{-1}(A \otimes B)(P \otimes Q) &= (P^{-1} \otimes Q^{-1})(A \otimes B)(P \otimes Q) \\
&= (P^{-1}AP) \otimes (Q^{-1}BQ) \\
&= J_A \otimes J_B
\end{aligned} \tag{A.34}$$

A Schur form for  $A \otimes B$  can be derived similarly. For example, suppose that  $P$  and  $Q$  are unitary matrices that reduce  $A$  and  $B$  respectively, to Schur (triangular) form, i.e.,  $P^HAP = T_A$  and  $Q^HBQ = T_B$  (and similarly if  $P$  and  $Q$  are orthogonal similarities reducing  $A$  and  $B$  to real Schur form). Then:

$$\begin{aligned}
(P \otimes Q)^H(A \otimes B)(P \otimes Q) &= (P^H \otimes Q^H)(A \otimes B)(P \otimes Q) \\
&= (P^HAP) \otimes (Q^HBQ) \\
&= T_A \otimes T_B
\end{aligned} \tag{A.35}$$

9. Let  $A \in \mathbb{R}^{n \times n}$  and  $B \in \mathbb{R}^{m \times m}$ . Then:

$$b. \text{Tr}(A \otimes B) = (\text{Tr}A)(\text{Tr}B) = \text{Tr}(B \otimes A) \tag{A.36}$$

$$c. \det(A \otimes B) = (\det A)^m (\det B)^n = \det(B \otimes A) \tag{A.37}$$

## A. 3. Inverse Matrix Operations

In a matrix domain, whether or not a given  $n \times n$  (square) matrix  $A$  has a multiplication inverse matrix (that is, a matrix  $A^{-1}$  such that  $AA^{-1} = I_n$ ) must be considered. Interestingly, not all square matrices have multiplicative inverses, although most do.

### A.3.1. Inverses of Larger Matrix

Let  $A$  be an  $n \times n$  matrix. Then, the method for finding the inverse of a matrix (if it exists) (inverse method) is as follows [106]:

Step 1: Augment  $A$  to an  $n \times 2n$  matrix, whose first  $n$  columns constitute  $A$  itself and whose last  $n$  columns constitute  $I_n$ .

Step 2: Convert  $[A|I_n]$  into reduced row echelon form.

Step 3: If the first columns of  $[A|I_n]$  cannot be converted into  $I_n$ , then  $A$  is singular. Stop.

Step 4: Otherwise,  $A$  is non-singular, and the last  $n$  columns of the augmented matrix in reduced row echelon form constitute  $A^{-1}$ . That  $[A|I_n]$  row reduces to  $[I_n|A^{-1}]$ .

For example,

$$A = \begin{bmatrix} 4 & 2 & 8 & 1 \\ -2 & 0 & -4 & 1 \\ 1 & 4 & 2 & 0 \\ 3 & -1 & 6 & -2 \end{bmatrix} \quad (\text{A.38})$$

Beginning with  $[A|I_4]$  and simplifying the first two columns, obtains:

$$\begin{array}{cccc|cccc}
1 & 0 & 2 & -1/2 & 0 & -1/2 & 0 & 0 \\
0 & 1 & 0 & 3/2 & 1/2 & 1 & 0 & 0 \\
0 & 0 & 0 & -11/2 & -2 & -7/2 & 1 & 0 \\
0 & 0 & 0 & 1 & 1/2 & 5/2 & 0 & 1
\end{array} \tag{A.39}$$

Continuing on to the third column, it can be seen that element (3, 3) is zero. Thus, a type (I) operation cannot be used to make the pivot 1. As the element (4, 3) is also zero, no type (III) operation (switching the pivot row with a row below it) can make the pivot non-zero. In summary, there is no way to transform the first four columns into the identity matrix  $I_4$  using the row reduction process, and therefore the original matrix  $A$  has no inverse.

### A.3.2. System Solving using the Inverse of the Coefficient Matrix

$AX = B$  corresponds to a system where the coefficient matrix  $A$  is square. If  $A$  is non-singular, then the system has a unique solution ( $X=A^{-1}B$ ). Meanwhile, if  $A$  is singular, then the system has either no solutions or an infinite number of solutions. Hence,  $AX = B$  has a unique solution if and only if  $A$  is non-singular.

Proof:

If  $A$  is non-singular, then  $A^{-1}B$  is a solution for the system  $AX = B$  because  $A(A^{-1}B) = (AA^{-1})B = I_n B = B$ . To show that this solution is unique, suppose  $Y$  is any solution to the system; that is, suppose that  $AY = B$ . Then both sides of  $AY = B$  on the left by  $A^{-1}$  can be multiplied to get:

$$A^{-1}(AY) = A^{-1}B \Rightarrow (A^{-1}A)Y = A^{-1}B$$

$$\Rightarrow I_n Y = A^{-1}B$$

$$\Rightarrow Y = A^{-1}B \tag{A.40}$$

Therefore,  $A^{-1}B$  is the only solution of  $AX = B$ .

Conversely, if  $A$  is singular then  $\text{rank}(A) < n$ , and so not every column of  $A$  becomes a pivot column in the row reduction of the augmented matrix  $[A|B]$ . Thus, it can be presumed that  $AX = B$  has at least one solution. Then this system has at least one independent variable (which can take on any real value), and hence, the system has an infinite number of solutions.