Partial Fingerprint Recognition Through Region-Based Approach

by

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Declaration

I hereby declare that this thesis contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

Omid Zanganeh

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- **O. Zanganeh and S. Ibrahim**, *"Adaptive Image Steganography Based on Optimal Embedding and Robust Against Chi-square Attack"*, Information Technology Journal, vol. 10, no. 7, pp. 1285-1294, 2011.

- **H. M. Sardroudi, S. Ibrahim, and O. Zanganeh**, *"Robust Database Watermarking Technique over Numerical Data"*, Journal of Communications and Information Sciences, vol. 1, no. 1, pp. 30-40, April 2011.

- **O. Zanganeh and S. Ibrahim**, *"Image Steganography Based on Adaptive Optimal Embedding"*, in International Conference on Computer Science and Convergence Information Technology (ICCIT), Korea, 2010, pp. 600-605.

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Abstract

Traditional person recognition methods rely on knowledge/possession-based approaches such as password and access cards. However, these kinds of approaches suffer from the threat that they might be shared or stolen. Thus, differentiating between authorized and unauthorized users is very difficult (if not impossible). Biometrics on the other hand offers a means to reliable person recognition which overcomes the previously mentioned issues of traditional methods. In modern days the rise of computer tools have made it achievable to make recognition processing fully automated.

Fingerprints were one of the first biometric traits to be accepted and utilized by law enforcement agencies. Despite popular belief and years of research, automatic fingerprint recognition is not a foolproof system and is yet an open and challenging problem. One of the most prominent issues in automatic fingerprint recognition which prevent it from being foolproof is that impressions of different fingers may be more similar to each other than the impressions of the same finger (inter-class similarity). Likewise, different acquisition of the same finger may be dissimilar from each other compared to the impressions taken from different fingers (intra-class variation). Obviously, the above statement directly relates to how the similarity or dissimilarity of fingerprints is defined. One of the main factors leading to high intra-class variation is the low quality of the fingerprints. The performance of the fingerprint recognition system deeply depends on fingerprint image quality. The matching accuracy of automated fingerprint recognition system decreases significantly when the quality of the fingerprint is poor. For example, a fingerprint is considered of poor quality due to the existence of noise and scars on it which in these cases manual recognition achieves better accuracy than automated systems.

Dealing with intra-class variation and inter-class similarity is even more challenging when it comes to partial fingerprint recognition. The issues of partial

fingerprint recognition is outwardly similar to the issues of full fingerprint matching, however it keeps its own unique characteristics e.g. unavailability of all the features, covering small part of the finger, and being unclear and/or distorted. Although it is claimed by researchers that some regions of a fingerprint provide more distinguishing characteristics than others, uncertainty in what regions are available in a partial fingerprint increases the probability of misrecognising it. Also, different types of features can be extracted from a full fingerprint but not all of them are available in a partial fingerprint. Thus, correct recognition of partial fingerprint is dependent on proposing a method which is robust to the missing features and image quality as well as being able to extract the available distinguishing features, independently from partial fingerprint size and shape.

In order to reasonably define the similarity in full and partial fingerprints, distinguishing the intra and inter cases, and to advance science in this field, the following contributions are presented:

Partial fingerprint alignment:

Maltoni et al. [1] and Pankanti et al. [2] induced designers to look for additional distinguishing fingerprint features beyond minutiae (the widely-used fingerprint feature). The authors found that a grey-level fingerprint image contains richer, more discriminatory information than only the minutiae location. Considering the rich information provided by the grey-level fingerprint image, it can be used to align the fingerprints. Two fingerprints should be aligned properly in order to measure their similarity. The previously developed fingerprint alignment methods, including minutia and non-minutia feature based alignment methods, are not suitable for partial fingerprints. These methods are dependent on the fingerprint's particular features such as reference points which might not be available in par-

[1] D. Maltoni, D. Maio, A. K. Jain, and S. Prabhakar, Handbook of Fingerprint Recognition, 2nd ed. New York: Springer, 2009.

[2] S. Pankanti, S. Prabhakar, and A. K. Jain, On the individuality of fingerprints," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, no. 8, pp. 1010-1025, 2002.

tial fingerprinting. Also, feature selection is a vital step in alignment (the same as for the matching process). Thus, the information/features used for alignment plays an important role in accurate alignment which is very important, specially in region-based matching (since corresponding regions will be compared). In the alignment stage, two methods are proposed which are suitable for partial and full fingerprint alignment. Here, the information obtained in the alignment step is used as the first level of fingerprint recognition. The first method is based on using the singular points and ridge structure of a fingerprint by cropping different regions with different sizes from query fingerprints and computing the similarity of these regions with registered fingerprints at different angles. The rotation angle that provides the highest correlation is considered as the rotation difference of query and registered fingerprint. However, as singular points are not always available in partial fingerprinting and additionally the correlation maximum score of comparing two regions might not always be the correct correlation. In some cases, it is possible that more than one peak (of approximately the same height) exists. That increases the probability of choosing the incorrect peak. Also a situation may happen whereby the correct peak is slightly lower than the false peak. To combat this in the second method, the consistency of corresponding regions located on the registered fingerprint is considered. By using the information provided from the alignment method, a Neural Network classifier is used to learn the behaviour of intra and inter comparisons in alignment. This classifier is used as the first-level of matching to reject/accept cases that do not need any further processing to be recognised.

Defining the similarity between fingerprints:

There is no agreed definition for the term *similarity*, between researchers in terms of defining the similarity between fingerprints. As a matter of fact, an algorithm should be defined to assign high similarity scores to different captured

fingerprints from the same finger even if they have high intra fingerprint variation. If the similarity could be defined in such a way that it could cover high variation between fingerprints of the same finger and low variation between fingerprints of different fingers, then the system error could be maintained close to zero. In other words, the fingerprints from the same finger are supposed to be more similar to each other compared to the fingerprints from different fingers and the similarity measurement needs to be defined as such to assign high similarity to the fingerprints of the same finger regardless of the variability in the capture environment which introduces unpredictable errors in the captured image; and also assigns low similarity to the fingerprints of a different finger even if they appear to be very indistinguishable. The proposed similarity measurement method is based on the texture characteristic of the fingerprint which is claimed by researchers to provide more reliable and distinguishing information. Reliability and distinguishability of the texture based features compared with other available features is discussed. Also the different texture features are compared and investigated in order to identify the best texture/region based feature of the fingerprint. As a result the similarity is mainly computed based on the Normalized Cross Correlation (NCC) of the fingerprint (sub-regions) along with other techniques to lower the effect of high intra-class variation and low-inter class similarity and consequently, better distinguishing the intra and inter fingerprints even in low quality partial fingerprint. Also, the similarity of the two fingerprints is computed in such a way that the distorted regions are assigned low weights so they will not significantly skew the final similarity of two fingerprints.

The main objective of this research relates to partial fingerprint recognition and the proposed method reasonably addresses the difficulties in partial fingerprint (as well as full fingerprint) matching. In all parts, the aim was to make it independent from any particular feature of the fingerprint to adaptively deal with the

partial fingerprint size. The proposed method uses the fingerprint ridge structure to obtain the characteristic information of the partial fingerprints. As mentioned, fingerprints ridge structure provides rich and distinguishing information and at the same time the similarity of partial fingerprint can be computed independently from region size, shape, and location in the fingerprint. Thus, unavailability of any particular feature such as reference points and minutiae will not be an issue and even if a small region is available, the matching can proceed. Also, there is always a mis-detection rate (however low) when extracting features like reference points and minutiae which might lead to falsely accepting or rejecting a query fingerprint. This is not an issue in the proposed method as it does not rely on any particular feature.

As a result, the experiments conducted on partial dataset generated from the FVC2002 (Fingerprint Verification Competition) dataset shows the effectiveness and improvement achieved through the proposed method with approximately an 8.5% better Equal Error Rate (in average) while being able to process almost 3 times more of the partial fingerprints in the dataset (regardless of their size) compared to the state-of-the-art method proposed by Abraham et al. [3].

[3] J. Abraham, J. Gao, and P. Kwan, Fingerprint matching using a hybrid shape and orientation descriptor. INTECH Open Access Publisher, 2011.

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Chapter 1

Introduction

1.1 Preamble

Trusted identification and verification is now vital for everyday activities such as performing a financial deal, proceeding to an airport check-in, or obtaining health and social services. The necessity of secure and reliable identification has led to an increased demand for recognition. In modern days, recognizing a person is vital, thus for many applications, guaranteeing the reliable identification is a requirement [1]. Unable to rightly recognize a person may lead to the lack of accessibility to the resources, violation of privacy of information and perhaps other failures such as deaths or loss of family. Identification becomes a complicated process when it has to be computerized with a high degree of precision. However, the automated recognition process should provide user convenience and should not overload users with system complexity.

Individuals have naturally recognized each other by their appearance, voice and context of their speech [2]. Verification in official activities, such as airport check-in control or in financial dealings, has typically depended upon the possession of something such as a passport or personal identification number (PIN). With the use of automated systems, person identification has to depend mostly on belongings

such as smart cards and on secrets such as security passwords or PIN, etc.

However, identification based on either belongings or on secret information such as a password only verifies that the ownership or the secret was provided at the time of the transaction. The main issue here is that ownership or knowing the secret does not confirm the proprietor is the genuine user. This essential problem with conventional methods created a disaster on 11 September 2001; a terrorist attack that led to the loss of life of 2966 people [3]. Some of the terrorist hijackers were on the Federal Bureau of Investigation (FBI) watch list, but they were using fake passports [4]. Judge Jean Louis Bruguiere (one of the most senior authorities on terrorism) stated that identification documents are as important as weaponry for the terrorists [5]. It could be determined that with no procedure to validate any link between a password or other identity devices and its proprietor, such a disaster is silently waiting to happen.

The need for a recognition with a high degree of confidence has motivated the adoption of biometric technological innovation in various applications. The term "biometrics" refers to a measurable characteristic that is unique to an individual such as a fingerprint, facial structure, the iris or a person's voice. Recognizing people based on their physical or behavioural features is the main objective of biometric technology. It is being approved by government and industry so that automated biometric recognition will likely become an essential part of life.

These days, biometric technology has been implemented in many applications. In general, these applications can be classified into four groups [6]. The first group of application is managing access to devices, such as signing into a laptop computer or a network [7]. The second group of application is managing accessible materials such as financial and medical care services [8, 9, 10]. The third is to confirm a claimed identity against an existing credential, such as at border control [11]. The fourth group is to recognize individuals, whose identity need to be established, most

often using central or distributed data sources. Identification of scammers [12] and army [13] uses of biometrics are illustrations of the fourth group.

Four main advantages of biometric identification compared to traditional methods are [14]: **user convenience:** e.g. no need to carry a card or remember a PIN, **better security:** e.g. only the authorized person can access the source (not the person who knows the secret key!), **better accountability:** e.g. difficult to deny access to resources, and **higher efficiency:** e.g. lower password maintenance overhead.

However, the ever increasing acceptance of biometrics has been misjudged to create the view that there are no remaining issues in automated identification of individuals [1]. A prime example of this is the misidentification of a suspect by the FBI when dealing with the Madrid terrorist attack in 2004 [15]. In this instance, the FBI wrongly arrested Brandon Mayfield in 2004. A fingerprint which was sent from Madrid connected him to the train bombing that killed 191 individuals and injured 2000 people. When the Spanish government recognized the fingerprint represents that of an Algerian, the Department of Justice of U.S. asked for Mr Mayfield to be released. What we can infer from the Mayfield story is that there is still an outstanding issue for fingerprint recognition to provide a high degree of confidence that automated fingerprint recognition results are accurate, effective and reliable, otherwise, fingerprint usage may be left behind if it is unable to come up to these expectations.

1.2 Issues and Challenges of Fingerprint Recognition

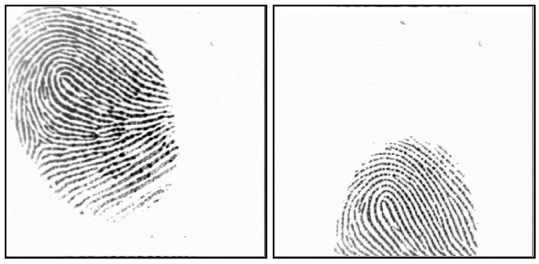
Everyday, a number of questions about a person's identity is being asked in the context of different applications. Fingerprints as one of the biometric traits has

been successfully used in a wide range of applications [16]. Its flattering depiction in crime movies and television shows (e.g. The Sentinel), leaves the impression that Automatic Fingerprint Identification System (AFIS) is a foolproof technology. That is not true and recognizing the identity of a person with a high degree of confidence is essential [14]. The level of confidence shows the degree to which a system can reliably determine whether a query biometric belongs to a registered biometric or not. Biometrics refers to the concept of identity, as a result, biometrics are often considered as a proxy for trustworthiness [17]. This role of biometrics leads to the requirement of a biometric recognition system with a high degree of confidence.

The ideal biometric recognition is that when a sample is provided to the system, it gives a correct decision. In fact a biometric system can be considered as a pattern classifier which inevitably makes some incorrect decisions [14, 18]. Although biometric recognition is successful in some niche areas and accepted as a unique characteristic for each individual, it is not yet recognised to be foolproof [19]. Issues leading to a non-foolproof recognition system have occurred in different stages of recognition. These stages are mainly: data capturing and pre-processing, feature extraction and matching [20, 18]. In the following sections, the main errors that could occur in these stages are discussed.

1.2.1 Data capture errors

In a fully automated biometric system, the data (sample) is captured without human supervision and support [14]. Thus, in the data capturing and pre-processing stage, the provided sample could differ from the ideal one due to problems such as: the size of the sensor used to capture the sample (information limitation), dry or moist fingers, poor finger placement (information limitation and orientation variance), dirt on the scanner surface, finger skin elasticity and worn ridge structure.



(a) poor fingerprint placement

(b) finger skin elasticity

(c) dry finger

(d) moist finger

(e) worn ridge

Figure 1.1: Examples of issues occurring to fingerprint images during data capturing stage

The sample provided in this stage is used in the next stage for feature extraction. Obviously, the more the sample suffers from the aforementioned problems, the more difficult it would be to handle it in the next stages. Figure 1.1 shows examples of the issues that happen in the data capturing and pre-processing stage.

Figure 1.1a shows two fingerprints that are misplaced on the sensor. In addition the quality of the image is low. Misplacing the finger on the scanner leads to information limitation (partial print) in this case. Full fingerprint matching is mature compared to a partial print [21]. Usually the assumption is that the two fingerprints are almost of the same size and include almost all the fingerprint area. This assumption is not valid. As a matter of fact, not only mis-placing the finger

on the scanner, but also the small sensing area in modern scanners will result in capturing a partial fingerprint (information limitation).

Miniaturization of the fingerprint scanners is one of the major reasons that led to small scanning areas These vary from 1" × 1" to 0.42" × 0.42" [21]. Fingerprint scanners with a sensing area smaller than 0.5" × 0.7", is considered to be the average fingerprint size [22], and can only capture partial fingerprints [21]. The smaller the area of the fingerprint is, the less discriminative information it provides for recognition (see Section 1.2.4 for details).

In addition, the orientation difference between the two images in Figure 1.1a and finger skin elasticity in Figure 1.1b make correctly comparing the two fingerprints more difficult for pixel-based algorithms. Figure 1.1b is an example of two images from the same finger which do not appear identical due to the finger skin elasticity on the scanner surface which is produced by non-orthogonal pressure of the finger against the fingerprint scanner.

1.2.2 Feature extraction errors

After capturing the biometric sample, the next process is the feature extraction. Depending on the quality of the captured image, the feature extraction algorithms may fail to extract a usable feature set. This error is knows as Failure To Process (FTP) [14]. The similarity of two fingerprints is computed based on the extracted feature set at this stage, therefore a high FTP errors result in not confidently computing the similarity score of the fingerprints and consequently increasing misrecognition rate in the system.

1.2.3 Matching errors

In any biometric system, physical characteristics of the individual are mapped into a template that is stored in the computer (hereinafter referred as registered/stored

template). The system compares the registered template to the presented template (hereinafter referred as query template) generating a similarity score. There are two types of matching system: verification, and identification. **Verification** is the process of *verifying if a user is actually who he/she claims to be.* This process consists of comparing a user registered template in the data base with the one provided by the user (query template). The comparison results in a similarity score which depending on the threshold depicts whether the user is really who he/she claims to be or not. **Identification** is the process of *finding to whom the provided biometric data belongs to.* In identification (unlike verification), the entire data base needs to be searched (not a one-to-one comparison). The best possible candidate is the one providing the highest similarity with respect to the query template.

The result of matching two fingerprints is generally a number between the interval $[0, 1]$. The closer the similarity score is to one, the more certain is the system that the two fingerprints come from the same finger. The decision based on the similarity score is regulated by using the threshold *"t"*. If the similarity of the two fingerprints is higher than the threshold, systems indicate them to be from the same finger and vice versa. At this stage, there are problems that affect the result of the system on the similarity score of two fingerprints which leads to mis-recognizing them to be from the same finger or not. **First**, due to the problems mentioned in Section 1.2.1 and Section 1.2.2, fingerprints acquired from the same finger are not identical. The fingerprints captured from different fingers are very similar and sometimes are assigned to a higher similarity score than the fingerprints captured from the same finger. Therefore, depending on how the similarity between fingerprints is defined (**second problem**), it can have a significant impact on the system performance. In fact, it is very difficult to define the similarity between fingerprints in such a way that could cover the variation

between the samples of the same finger. Hence, due to the lack of an appropriate similarity measurement technique, fingerprints that are in fact from the same finger may be assigned a similarity lower than similarity assigned to two fingerprints from different fingers. In this case, it is very likely that the two samples from the same finger be rejected by the system as being from different fingers. This is called *false-non-match* or *false-rejection* error. Likewise, there are fingerprints from different fingers that appear to be very similar and the system might assign them a high similarity score and mis-recognize them to be from the same finger. This is called *false-match* or *false-acceptance* error.

Regarding the matching errors, the verification and identification systems are introduced and the errors related to each system is discussed in next sections.

1.2.3.1 Verification errors

In the previous section, the errors that could happen in a one to one comparison (typical verification process) is discussed. Let a user's registered fingerprint template in the system and the feature set extracted from the query fingerprint be *"T"* and *"F"* respectively, the null and alternate hypothesis will be as follows [14]:

$H_0 : F \neq T$, extracted feature set *does not come from* the same finger as template.

$H_1 : F = T$, extracted feature set *does come from* the same finger as template.

The corresponding decisions is based on the similarity score of the two fingerprints and system threshold as: D_0 : non-match (rejected), and D_1 : match (accepted). These hypothesis lead to two type of errors [14]:

Type I: false-match (false accept), D_1 is decided when H_0 is true.

Type II: false-non-match (false reject), D_0 is decided when H_1 is true.

False-Match Rate (FMR, or False Accept Rate (FAR)) and False-Non-Match Rate (FNMR, False Reject Rate (FRR)) are the probability of type I and type II

errors, respectively.

$FMR = FAR = P(D_1|H_0)$, and $\qquad FNMR = FRR = P(D_0|H_1)$

1.2.3.2 Identification errors

The two types of error that could occur in a one to one comparison was discussed in the last subsection. In identification, the number of comparisons increase to the total number of templates ("N") in the dataset [23]. Thus identification error rate is dependant on the number of comparisons to make (number of templates in the dataset to search for).

If FMR_1 is the probability of false match in a single one-to-one authentication system, then the probability of not making a false match in this system is $1 - FMR_1$. Thus, the likelihood of successfully avoiding this in consecutive N attempts is= $(1 - FMR_1)^N$. FMR_N, which is the probability of making at least one false match when searching a database containing N different templates, is $FMR_N = 1 - (1 - FMR_1)^N$ [24]. Likewise, the probability of making at least one false non-match when searching a database containing N different templates is $FNMR_N = 1 - (1 - FNMR_1)^N$. *It can be inferred that compared to authentication, the problem of making an incorrect match is worse for identification.*

1.2.4 Issues with partial fingerprint recognition

The issues with partial fingerprint recognition is primarily similar to the issues related to full fingerprint matching. However due to its unique characteristics of being partial, it presents additional obstacles to the implementation of such partial print recognition [21].

Matching a partial print to a pre-registered full fingerprint is usually applicable in forensic applications. In the majority of cases, partial fingerprints obtained from crime scenes are broken and unclear. Therefore, useful parts of the partial

print is limited. Lately, this problem has become important from a commercial point of view since fingerprint scanners can only capture a small part of the whole fingerprint [25].

Partial fingerprint recognition is challenging and complex since partial prints are often small (contain limited information of a full fingerprint), unclear, distorted, smudged, can overlap with other prints, and can contain artefacts from the capturing process [26]. Therefore, partial fingerprints are usually assumed to be of low quality. Recognising a low quality fingerprint, will be challenging since it is less similar to the other prints of the same finger and consequently result in increasing the *FNMR*. Compared to a full fingerprint, there is less information available in a partial fingerprint which makes it more challenging to correctly recognise it and differentiate it from the prints of different fingers. Uncontrolled scanning environments result in unspecified orientations of obtained partial fingerprints and also distortions are introduced due to characteristics of human skin such as elasticity. The partial fingerprints obtained from a crime scene are normally small and noisy [21, 25] and non-existence of singular points (core and delta) is likely, so a robust system that is independent of relying on these singularities is required [21, 25]. Figure 1.2 shows the singular points of the fingerprint. These points are considered to be one of the robust features of the fingerprint (if available due to the sensor size and poor finger placement) against the above mentioned problems in Section 1.2.

In addition to that, it is not known *which part* of the finger the partial fingerprint belongs to. Obviously, matching different parts of two fingerprints (from the same finger), will result in mis-recognising them to be from different fingers. Therefore, identifying the corresponding regions of the partial fingerprint is a critical issue especially when the partial fingerprint is of a very small size and there is not adequate discriminatory information to utilize.

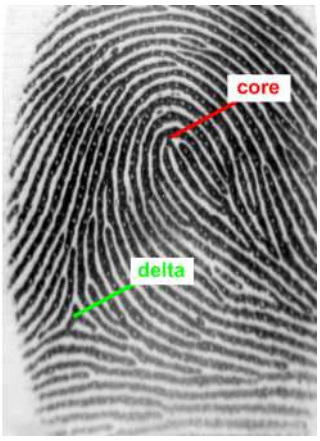


Figure 1.2: Singular points in a full fingerprint image

Due to the information limitation in partial fingerprints, it is difficult to reduce the variation between the partial prints of the same finger. As discussed in Section 1.2.1, orientation difference is one of the issues that makes partial prints from the same finger assigned a low similarity score. In order to compensate for this issue, it is essential to align the partial prints in terms of orientation. Therefore, it is essential to take care of the orientation difference between partial prints *considering the information limitation.*

Furthermore, quality of the fingerprints may vary in different regions. Figure 1.3 shows an example of the fingerprint images where the quality of different regions vary. In full fingerprints, even if the quality of some parts of the image is low, it is quite likely to find enough good quality parts too. However, in partial prints, utilizing the low quality parts of the image is essential as it might be the only available information. In other words, making a correct decision can be difficult due to the small amount of good quality regions in partial pints.

Considering the issues mentioned above; including the information limitation, and likelihood of small good quality regions on the fingerprint, it is essential to determine the most discriminative characteristic of a fingerprint that makes it different from other fingerprints. In other words, the less valid information about

Figure 1.3: A partial and a full fingerprint with varying quality in different parts of the image

the fingerprint is provided, the more difficult it is to correctly recognise it and at the same time, the more important it becomes to identify the most discriminative characteristic of the available information. As mentioned in Section 1.2.3.1, the similarity score of comparing two fingerprints is used to decide whether two fingerprints are from the same finger or not while the similarity score is computed based on the discriminative feature mentioned above. However, there is not a common agreement on how the similarity score is defined. Therefore, by accurately defining the similarity of fingerprints based on the features that highly reflect the characteristic of the fingerprint, the system errors (both *FMR* and *FNMR*) can be reduced.

1.3 Motivation

Biometrics consists of many automated methods with the aim of reliably authenticating or identifying a person based on one or more physiological or behavioural characteristics [27]. As stated by Busch [28], *"the main advantage of biometric authentication is that it reduces the risk of information (passwords) or tokens (keys or chip cards) being stolen or passed on to unauthorized people"*. Using a unique physical biometric attribute, such as a fingerprint, to easily verify *"he is who he*

claims to be" is the best and most effortless solution for recognition in the market [27]. Although biometric technology has been around for a while, biometrics is now more readily available and practical even for small businesses due to the cost reduction and modern advances in miniaturization [27, 14, 28].

Due to the popularity of smart phones, it is possible to deploy mobile biometric recognition. In various cities in Germany, police has introduced mobile fingerprint recognition which enables immediate recognition over mobile networks [28]. However, such a technology could be used for many applications and an increasing demand for safe and secure deployment is now driving research in this rapidly growing area [28]. Among all the biometrics (DNA, iris, ear, palm, etc.) fingerprint matching is generally accepted for its high distinctiveness, and permanency [29].

The usual assumption is that the two fingerprints will be of the same size and cover almost all the fingertip area, but that assumption is not defensible. Miniaturization of the scanners causes a partial/fragment record of the fingerprint available. In addition, due to the presence of low quality regions in the fingerprint which are discarded (refer to Figure 1.3 in Section 1.2.4), the remaining usable regions may not be bigger than a partial fingerprint.

However, most of the current fingerprint recognition systems work only on parts of the available information of the biometric [30]. Using partial fingerprint reduces the useful features that could be used for recognition. In other words, using all the available information will improve the distinguishing capability of the systems, especially when the population is large. In order to be able to have an accurate recognition in a large population, the system should be able to reveal large amounts of useful features which reflect the individual characteristics of the biometric sample in the population. Otherwise, the reduction will increase the probability of making incorrect matches. This could be worse for identification compared to authentication; since in identification the entire database is searched

which increases the probability of incorrect matching. Compared to authentication, when searching a database of size N in identification, the systems needs to be approximately N times better to achieve comparable probabilities in making incorrect matches. As the database grows larger, the chance of making incorrect match also grows roughly in the same proportion. These chances also grow in proportion to the number of searches that are conducted against the database. However, maintaining very low false matches/non-matches is crucial regardless of the number of stored templates in a database.

1.4 Research Objectives

As mentioned in Section 1.3, a reliable biometric recognition system is now in high demand and using a unique biometric trait such as a fingerprint to identify an individual is one of the most effortless solutions in the market. Although biometric recognition has its advantages compared to password or token based recognition systems (as it is not to be stolen or forgotten), it has its unique difficulties. One of these difficulties is due to events which damage/alter the finger skin such as burns or scalds. That, in addition to the matching errors mentioned in Section 1.2 (intra fingerprint variation), increases the probability of mis-recognising a pair of fingerprints to be from different fingers while they are in fact from the same finger (high FRR). On the other hand, the algorithm used to assign a similarity score to a pair of fingerprints, might assign a high similarity score to fingerprints from different fingers due to the similarity of their extracted features (high FAR due to the inter fingerprint similarity). Therefore, the aim of the objectives in this research are to provide high recognition accuracy by taking care of the high intra fingerprint variation and high inter fingerprint similarity. The objectives are defined as follows:

1. Propose a partial fingerprint alignment technique (considering the limited information availability) which is also suitable for full fingerprints.

2. Propose a new similarity measurement technique that is suitable for partial and full fingerprints.

1.5 Research Contributions

The main contributions of this thesis can be summarized as follows:

1. **Partial fingerprint alignment:**

   Maltoni et al. [14] and Pankanti et al. [30] induced designers to look for additional fingerprint distinguishing features beyond minutiae (the widely-used fingerprint feature). Also, as stated in [31, 32], a grey-level fingerprint image contains richer, more discriminatory information than only the minutiae location. Considering the rich information provided by the grey-level fingerprint image, it can be used to align the fingerprints. Two fingerprints should be aligned properly, in order to measure their similarity. The previously developed fingerprint alignment methods, including minutia and non-minutia feature based ones, are not suitable for partial fingerprints. These methods are dependent on the fingerprint's particular features such as reference points which might not be available in a partial fingerprint. Also, feature selection is a vital step in alignment (the same as for the matching process). Thus, the information/features used for alignment plays an important role in accurate alignment which is very important especially in region-based matching (since corresponding regions will be compared). In the alignment stage, two methods are proposed which are suitable for partial and full fingerprint alignment. Also, the information obtained in the alignment step is used as the first level of fingerprint recognition. The first method is based on using the

fingerprint singular points and ridge structure by cropping different regions with different sizes from query fingerprints and computing the similarity of these regions with registered fingerprints in different angles. The rotation angle that provides the highest correlation is considered as the rotation difference of query and registered fingerprints. However, the singular points are not always available in partial fingerprints and additionally the correlation maximum score of comparing two regions might not always be the correct correlation. In some cases, it is possible that more than one peak (of approximately the same height) exists. That increases the probability of choosing the incorrect peak. Also a situation may happen that the correct peak is slightly lower than the false peak. Thus, in the second method the consistency in corresponding regions located on the registered fingerprint is considered. By using the information provided from the alignment method, a Neural Network classifier is used to learn the behaviour of intra and inter comparisons in alignment. This classifier is used as the first-level of matching to reject/accept cases that do not need any further processing to be recognised.

2. **Similarity measurement technique for partial and full fingerprints:**

   There is no agreed definition for the term *"similarity"* between researchers in terms of defining the similarity between fingerprints. As a matter of fact, an algorithm should be defined to assign high similarity scores to different captured fingerprints from the same finger even if they have high intra fingerprint variation. If the similarity could be defined in such a way that it could cover high variation between fingerprints of the same finger and low variation between fingerprints of different fingers, then the system error could be maintained close to zero. In other words, the fingerprints from the same finger are supposed to be more *similar* to each other compared to the fin-

gerprints from different fingers and the similarity measurement needs to be defined as such to assign a high similarity to the fingerprints of the same finger regardless of the variability in the capture environment which introduces unpredictable errors in the captured image; and also assigns low similarity to the fingerprints of different fingers even if they appear to be very indistinguishable. The proposed similarity measurement method is based on the texture characteristic of the fingerprint which is claimed by researchers to provide more reliable and distinguishing information. Reliability and distinguishability of the texture based features compared with other available features is discussed. Also the different texture features are compared and investigated in order to identify the best texture/region based feature of the fingerprint. As a result, the intra-fingerprint variation and inter-fingerprint similarity can be taken care of. The similarity of the two fingerprints is computed in such a way that the distorted regions are assigned low weights so they will not significantly skew the final similarity of two fingerprints.

The main objective of this research relates to partial fingerprint recognition and the proposed method reasonably takes care of the difficulties in partial fingerprint (as well as full fingerprint) matching. In all parts, the aim was to make it independent from any particular feature of the fingerprint to adaptively deal with the partial fingerprint size. The proposed method uses the fingerprint ridge structure to obtain the characteristic information of the partial fingerprints. As mentioned, a fingerprint ridge structure provides rich and distinguishing information and at the same time the similarity of partial fingerprint can be computed independently from region size, shape and location in the fingerprint. Thus, unavailability of any particular feature such as reference points and minutiae will not be an issue and even if a small region is available, the matching can proceed. Also, there is always a mis-detection rate (however low) when extracting features like reference points

and minutiae which might lead to falsely accepting or rejecting a query fingerprint. This is not an issue in the proposed method as it does not rely on any particular feature.

1.6 Thesis Organization

This thesis is organized into 6 chapters, and the inter-relationship between the chapters is depicted in the Figure 1.4.

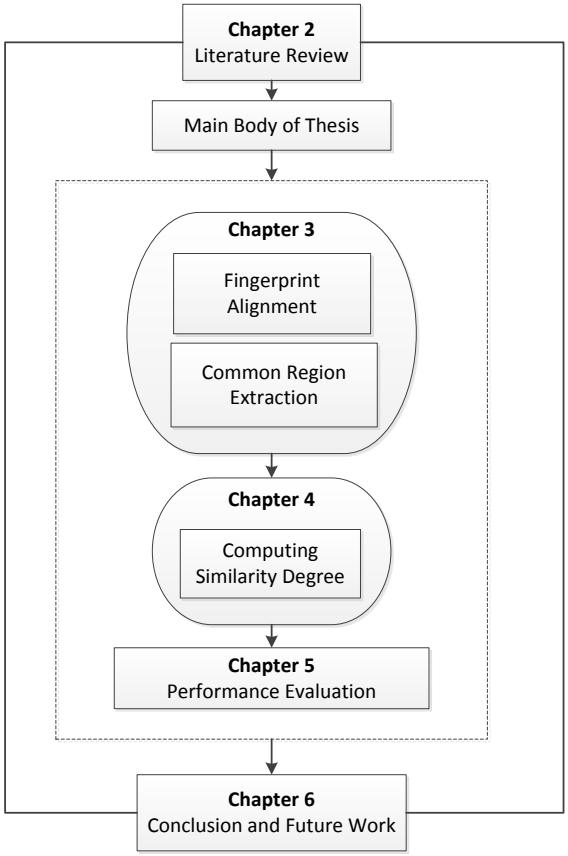


Figure 1.4: Thesis organization.

Chapter 2 describes the literature review on existing related work in biometric recognition and especially with the field of fingerprint recognition. The major aim

of the literature review is to acquire an idea of the work that has been done before by other researchers and gain an insight into the contribution of this thesis in the context of other existing work. It outlines the achievements of the previous methods and other researchers' works in the same domain and analyses the pros and cons of these methods. More importantly, it highlights the problems which remain outstanding.

Chapter 3 addresses the first objective by describing the proposed alignment method which is suitable for both partial and full fingerprints. Followed by process of extracting the fingerprint common region. Computing the similarity of fingerprints (second objective) is discussed in Chapter 4.

As both the alignment and similarity measurement needs to be performed in order to enable the system to make match/non-match decision based on the two fingerprints, the experimental result in presented in the next chapter (Chapter 5). The results of the proposed partial fingerprint recognition method is presented in Chapter 5 and results are compared with other methods including those based on minutiae and non-minutiae features.

Chapter 6 presents the conclusion of this thesis. It provides the summary of the results achieved, outlines its contributions, and provides an insight into future issues that are worthy of further investigation.

Chapter 2

Background and Related Work

2.1 Preamble

The foundation for this research is laid in this chapter, and the related work is discussed. A comparison of the most-used biometric traits is conducted (Section 2.2) which is followed by a discussion on the fingerprint collection and enhancement in Section 2.3 and Section 2.4 respectively. The quality measurement used to evaluate the quality of a fingerprint locally and globally is discussed in Section 2.5 followed by the available features in fingerprinting (Section 2.6). The advantages and disadvantages of the three major categories of fingerprint matching approaches in the literature which are minutiae-based, ridge feature-based and correlation-based approaches are discussed (Section 2.7) in order to identify the appropriate approach to address the issues of partial fingerprint matching. The issues with partial fingerprint recognition is primarily similar to the issues related to full fingerprint matching, however due to its unique characteristics of being partial it presents additional obstacles to the implementation of such partial print recognition [21] (Section 1.2.4). Among the three categories of fingerprint matching, a correlation-based approach (Section 2.7.4) that treats the fingerprints as an image and uses all the pixel intensity values to reflect the characteristic of a fingerprint is more ap-

propriate for partial fingerprint matching. That is due to utilizing all the available information of the fingerprint that is obtained though fingerprint texture as well as not being dependant on any particular fingerprint feature such as singular or minutiae points. The performance metrics used to evaluate the fingerprint matching systems are presented in Section 2.8 followed by the conclusion in Section 2.9.

2.2 Biometric Traits

Biometric identifiers are divided into two categories of physical and behavioural [33]. Physical biometrics refers to physical traits of an individual used for identification such as: DNA, ear, face, fingerprint, hand geometry, iris, and retina. Likewise, behavioural biometrics refers to the behavioural traits of an individual used for identification such as: gait, signature, and voice (Figure 2.1 shows examples of these traits). All biometrics recognition systems are a measurement to distinguish between a persons' biometric trait and that of someone else's trait. In fact, to identify a person, any physical or behavioural biometric trait can be used if it has the following requirements [14]:

- **Universality:** every individual should have that property. In other words, if a person is going to use a biometric system, he/she should possess the trait that the system is designed based upon. A system based on fingerprinting cannot be used in a population where people suffer from hand-related disabilities.

- **Individuality/Uniqueness:** the trait that a system is being designed based upon, should be sufficiently different for any two individuals so they can be distinguished.

- **Permanence/Persistence:** it relates to the manner that a trait may change over time and how well it resists the effect of time (generally speaking of

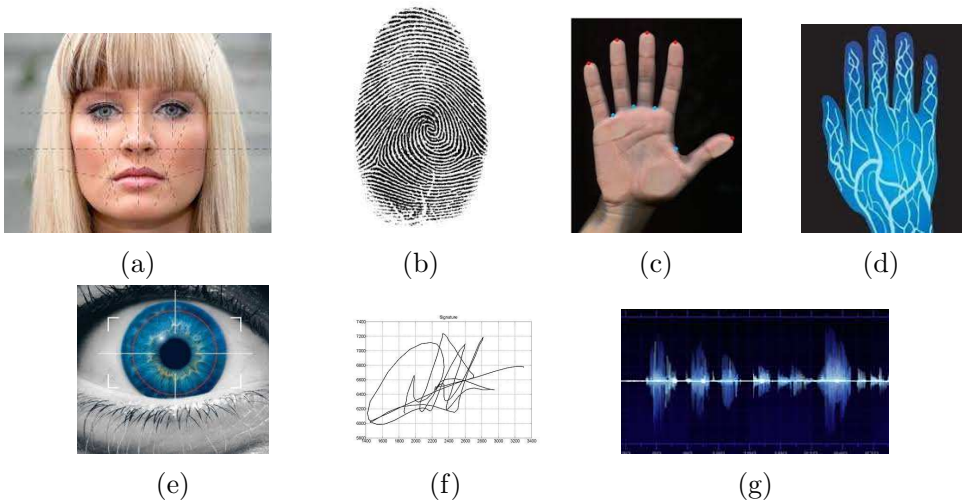


Figure 2.1: Examples of biometrics traits. a) face, b) fingerprint, c) hand geometry, d) hand/finger vein, e) iris, f) signature, g) voice

"ageing"). So the selected trait should be invariant over time.

- **Collectability/Measurability:** this property refers to the ease of acquisition and measure of the trait. It must be non-intrusive to collect, reliable, robust, and cost effective for recognition applications.

In addition, three other properties need to be considered to select a trait for biometric recognition [34]. First, **performance:** which refers to the system accuracy, speed, and robustness to the operational and environmental factors. Second, **acceptability:** to which level users accept to use it in their daily life; and third, **circumvention:** how easy it is to circumvent the system.

There is no ideal biometric trait that satisfies all the mentioned requirements. However, a practical trait should have a reasonable accuracy, user acceptance, and sufficient resistance against fraudulent methods [34]. Various biometric traits are used in different applications. Although each trait has its strength and weakness, the choice depends on the application and properties of that trait [14].

As Table 2.1 indicates, biometric traits have different levels in terms of universality, individuality, permanence, etc. Out of all the biometrics, fingerprint has a

Table 2.1: Comparison of biometric traits. Uni., Indi., Perm., Coll., Perf., Acc., and Circ. represent universality, individuality, permanence, collectability, performance, acceptability, and circumvention respectively. H, M, and L indicate High, Medium, and Low respectively [14].

Trait \ Attributes	Uni.	Indi..	Perm.	Coll.	Perf.	Acc.	Circ.
Face	H	L	M	H	L	H	H
Hand geometry	M	M	M	H	M	M	M
Hand/Finger vein	M	M	M	M	M	M	L
Iris	H	H	H	M	H	L	L
Signature	L	L	L	H	L	H	H
Voice	M	L	L	M	L	H	H
Fingerprint	M	H	H	M	H	M	M

reasonable balance between all the desirable properties. Excluding hand-related disabilities, every human being has fingers and hence fingerprints (**universality**). Fingerprints are **distinct** and **permanent** (even if it temporarily changes, it will reappear again after awhile). Leung et al. stated that the chance of two fingerprints being identical is 1 in 1.9×10^{15} [35, 36]. Fingerprints can be easily **collected** by a live-scanner which is affordable and **accepted** by many users in todays world.

Among the mentioned seven biometric traits in Table 2.1, iris and fingerprint have attracted more of researchers' attention than others. Both iris and fingerprint show high level of individuality, permanency, and performance. Although both of them have the medium rank in collectability, nowadays fingerprint scanners are found more acceptable, affordable, and convenient by users compared to iris scanners [14]. In terms of universality, circumvention, and acceptability, iris has better ranking in first two attributes whilst fingerprint has more user acceptability. As mentioned, the best biometric trait is defined according to the application requirement by considering the mentioned attributes. For instance, fingerprint systems show good **performance** and are robust against forgery (to other traits) [14]. However, fingerprint is not suitable for surveillance applications as the scanner cannot capture the fingerprints from a distance and without the

person awareness [37].

As indicated in Table 2.1, one of the attributes that biometric traits are compared is *"collectability"*. Fingerprint has a lower collectability rate compared to face and signature. However, face and signature both have lower performance and individuality than fingerprint. In next section, how fingerprints are collected is discussed. Fingerprint collection/acquisition is the first step in a fingerprint matching system.

2.3 Fingerprint Collection/Acquisition

Traditionally, fingerprint images were captured by law enforcement agencies by using the so-called *"ink-technique"* in which the person's finger was smeared with ink and rolled on the card. The card will then be scanned by a general purpose scanner to make a digital copy [14]. This kind of capturing is called off-line fingerprint acquisition. A particular case of off-line acquisition is the acquisition of latent fingerprints (fingerprint captured from a crime scene). Nowadays fingerprints are captured using an *on-line* or *live-scan* fingerprint sensor which is widely used in commercial and civil application. The sensors are based on optical, capacitance, ultrasonic, thermal, and other techniques used to capture images. Use of on-line scanners became popular due to its convenience, user acceptance, low cost, and reliability. Obviously, it is not expected from a user to smear his finger with ink every time he wants to login to his personal computer!

Beyond the type of fingerprint scanner, an important property of a scanner is the *image resolution* and *size of the scanner surface*. The scanner resolution is specified by number of pixels/dots per inch (p/dpi). 250 to 300 dpi is the minimum resolution that allows extracting minutiae and other features (refer to Section 2.6 for available features on fingerprints) from fingerprint. 500 dpi is the FBI's standard resolution, however it is not enough to extract very low level

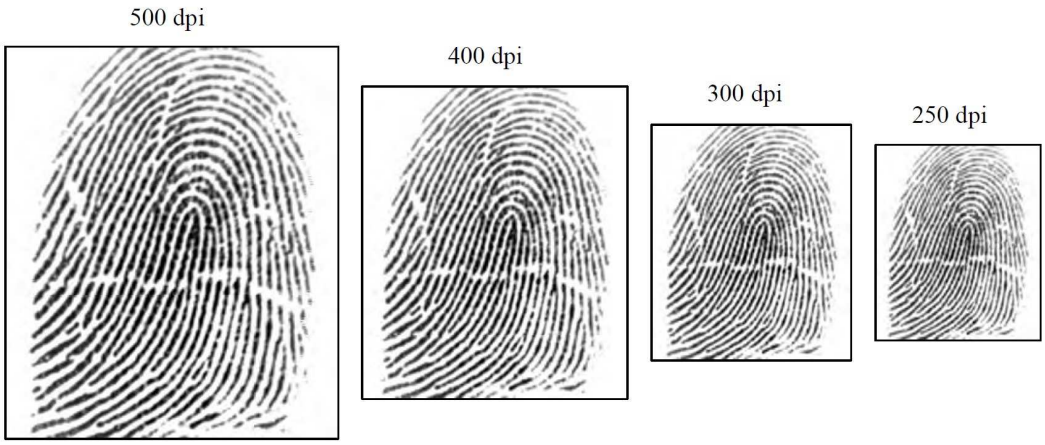


Figure 2.2: The same finger being captured at different sensor resolutions [14]

features from fingerprints (refer to Section 2.6.3). Figure 2.2 shows an example of fingerprints that are captured by an optical sensor with different resolutions. Obviously, the higher the image resolution is, the more reliable this fingerprint features can be recognised.

In addition to the image resolution, size of the scanner surface is another factor which can significantly effect the matching decision. It is generally assumed that a full fingerprint (which covers most of the fingertip area) is available for recognition. This assumption is not valid. The size of the new fingerprint sensors ranges from 1" × 1" to 0.4" × 0.4" due to the sensor miniaturization by manufacturers [21]. The smaller the sensor size is, the less fingerprint area is captured. Fingerprint sensors with the size of 0.5" × 0.7" is considered as an average size which only captures partial fingerprints [38] (refer to Sections 1.2.1 for data capture errors and Section 1.2.4 for the issues in partial fingerprint recognition).

After fingerprints are captured, the image processing techniques are performed on them. This step is to improve the quality of the fingerprint images and to make them ready for feature extraction (Section 2.6).

2.4 Image Processing

Image processing steps are taken to normalize the image contrast, lighting, and to remove undesired distortion from the image introduced during the data capture process. Different techniques such as: *Pixel Brightness Transformations*, *Geometric transformations*, *Local Pre-processing*, and *Image Restoration* are used as pre-processing operations to normalize the image pixel intensities [39, 40]. In case of fingerprint, a common step in fingerprint matching systems is to improve the quality of the fingerprint for further processes. The quality of the fingerprint plays an important role in fingerprint matching as the lower the quality of the fingerprint is, the more difficult it is to correctly extract the features and recognise it. Thus, fingerprint enhancement techniques are used to enhance the quality of fingerprints when possible. In the following, the fingerprint enhancement is discussed.

2.4.1 Fingerprint image enhancement

The performance of a fingerprint recognition system depends heavily on the quality of the fingerprint images which makes *fingerprint image enhancement* an important step in a recognition algorithm. It reduces the false features extracted by improving the quality of the images. Ideally, in a fingerprint image, ridges and valleys are separated and flow in a locally constant direction; which results in easy detection of features [34]. However, due to the issues mentioned in Section 1.2, (such as skin condition: dry or wet fingerprint), a significant number of fingerprints (approximately 10%) are of poor quality [14]. As a matter of fact, the quality of one fingerprint image may vary in different parts/regions and a fingerprint may contains regions of good, bad, or medium quality. Consequently, there could be well-defined regions (as in figure 2.3,a), recoverable regions (as in Figure 2.3,b), and unrecoverable regions (as in Figure 2.3,c). Quality of a fingerprint is generally

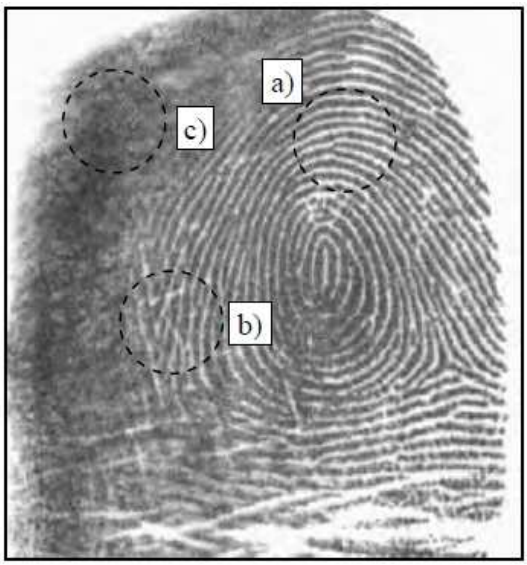


Figure 2.3: A fingerprint containing regions with different quality levels. a) a well-defined region, b) a recoverable region, c) an unrecoverable region [14]
.

assessed based on the three types of degradations [14]:

- First, ridges continuity (ridges having small breaks).
- Second, ridges not being completely separated (due to the noise on the scanner and fingerprint skin condition).
- Third, presence of cuts and bruises on the fingerprint.

Therefore, reliably extracting features from fingerprints of low quality becomes difficult, especially if the features are significantly dependent on the quality of the fingerprint.

Although fingerprint image quality can be improved by using enhancement techniques, its features are dependent on the image quality. In a typical minutiae-based technique (refer to Section 2.7.2), low quality images result in three main issues:

- First, extracting a significant number of spurious minutiae points.

- Second, missing a large number of genuine minutiae points.
- Third, errors in detecting minutiae location and orientation.

Therefore, in order to improve the reliability of the extracted features and the clarity of fingerprint ridge structures, enhancing the fingerprint image quality is necessary.

A survey of fingerprint enhancement techniques can be found in [34, 14]. These techniques can be classified into the general categories of *pixel-wise enhancement*, *multi-resolution enhancement*, *crease detection and removal*, and *contextual filtering*.

In pixel-wise enhancement techniques ([41, 42]), the new value of each pixel is only determined by its original value and some global parameters derived from the whole image (not the neighbour pixels) such as mean and variance in Equation 2.1. These techniques are mostly used as a preliminary step in more complete and sophisticated techniques [14]. Hong et al. [41] proposed an enhancement method that falls into this category. They determined the new intensity values of each pixel in an image as follows:

$$I'[x,y] = \begin{cases} m_0 + \sqrt{(I[x,y]-m)^2 \times v_0/v}, & \text{if } I[x,y] > m \\ m_0 - \sqrt{(I[x,y]-m)^2 \times v_0/v}, & \text{otherwise} \end{cases} \tag{2.1}$$

where m, v, m_0, and v_0 are the mean, variance, desired mean, and desired variance respectively. This technique can be applied according to the mean and variance of different parts of the fingerprint and thus applied in a local fashion [43]. The result of this enhancement is shown in Figure 2.4. However, this kind of operation only changes the pixel values and cannot fix the broken ridge and valley structure.

Multi-resolution enhancement techniques ([44, 45, 46]) are mostly used to remove noise from fingerprints by decomposing the image into sub-images which

(a) (b)

Figure 2.4: a) original image before and b) after enhancement by the method proposed by Hong et al. [41]. The new mean and variance are set to zero $m_0 = v_0 = 100$ [14]

.

enables to compensate for different noise types at different scales. Fronthaler et al. [46] (Figure 2.5) proposed an enhancement method which uses an image scale pyramid to divide the original fingerprint into three sub-images. Each sub-image corresponds to a different frequency band and is then treated through contextual filters [14].

Crease detection and removal techniques ([47, 48]) are used to detect and remove the creases from the fingerprint. With the provided contextual information (i.e. local orientation and frequency), these information can be used to detect and remove creases. However, in some cases the creases could be used as a feature to contribute in the matching process. Oliveira and Leite [48] (Figure 2.6) detect the creases by looking at the discordance between local orientation which is calculated at two different scales. As a matter of fact, in the detail scale, the local orientation changes show the presence of a crease and the overall ridge orientation which is estimated at a coarse scale [14].

Contextual filter techniques are the most widely used technique for fingerprint image enhancement [40]. In these techniques ([49, 50, 51, 52]), the characteristics of the filter change based on the local context which is defined according to the

(a) (b)

Figure 2.5: a) original image before and b) after enhancement by the method proposed by Fronthaler et al. [46].

.

Figure 2.6: An example of crease detection with the method proposed by Oliveira et al. [48]

local ridge orientation and frequency [14]. One of the popular methods based on contextual filtering in Fourier domain is proposed by Chikkerur et al. in 2007 [50, 53]. They have extended the application of Short Time Fourier Transform (STFT) which has been widely used in signal processing to 2-D fingerprint images. Their approach simultaneously estimates the intrinsic properties of the fingerprint such as the local ridge and orientation field to enhance the fingerprint. Their method consists of two stages; first, analysing the image by STFT and second is conducting contextual filtering and enhancing the fingerprint image based on the information provided from stage one. Figure 2.7 shows two fingerprint images before and after being enhanced by STFT method.

The STFT analysis results in orientation image, ridge frequency image, coherence image, and region mask. The orientation image represents the ridge orientation for every pixel in fingerprint. Ridge frequency image shows the average ridge distance in a local region [40]. Coherence image is used to compensate for the spurious artefact caused by discontinuity of the ridge flow around the region boundaries. The orientation, coherence, and frequency image are used to compute the region mask which is used to separate the foreground fingerprint image from the background image.

In the next section, fingerprint quality measurement techniques are introduced. As discussed in this section, some regions of the fingerprint are not recoverable even after applying enhancement algorithms. These regions affect the similarity score of two fingerprints (and lead to a false matching decision) since it is likely to extract false and spurious features from low/unrecoverable regions.

2.5 Quality Measurement

In the previous section, the definition of fingerprint image quality and the factors affecting the quality were discussed. Generally, the fingerprint image quality

(a) (b)

Figure 2.7: a) original image before and b) after enhancement by the STFT method proposed by Chikkerur et al. [50].

refers to the clarity of ridges and valleys structure which affects the extractability of fingerprint features such as singular points (refer to Section 2.6 for fingerprint features) [54]. The lower the quality of a fingerprint is, the more severely the system performance is degraded by making more false match/non-match decisions. Tabassi and Wilson [55] stated that the performance of a fingerprint recognition system is affected by the fingerprint image quality more than any other factors. This indicates the importance of estimating the quality and validity of the fingerprint images before matching. In this regard, the following four suggestions are proposed [56]:

- First, reject the very low quality fingerprints obtained from the enrolment process and/or accept only good quality samples.
- Second, identify and exclude the unrecoverable regions (refer to Figure 2.3).
- Third, adopt a matching strategy and similarity assignment to the quality of the fingerprints.
- Fourth, assign appropriate weights to the extracted features according to the

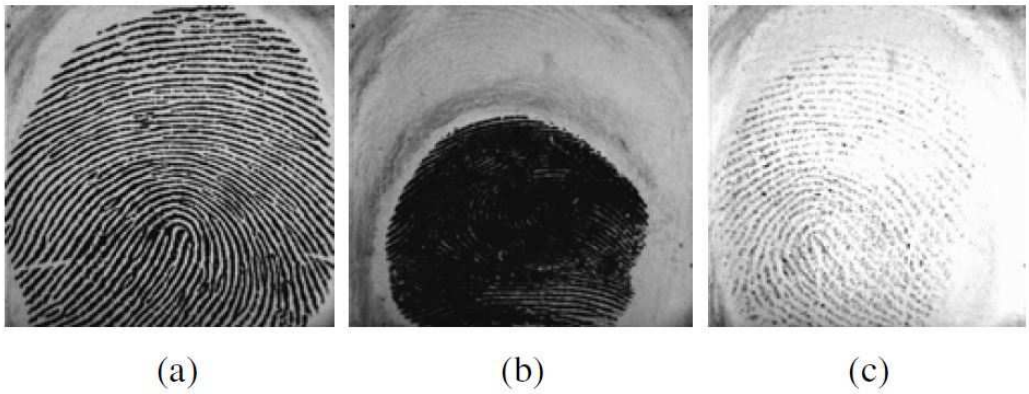


Figure 2.8: An example of a fingerprint with a) good dryness and wetness b) too wet, and c) too dry [56].

quality of the region they are extracted from.

Considering the above points, in partial fingerprint matching it might not be possible to reject the poor quality samples. Also, since the quality of different regions could vary in a fingerprint, the quality needs to be estimated locally. In following sections, some of the metrics used to measure the fingerprint quality are introduced.

2.5.1 Fingerprint dryness and wetness

Fingerprint dryness and wetness is one of the characteristics that show the fingerprint image quality. Fingerprint dryness and wetness can be measured by mean and variance of grey level intensities. A fingerprint that is too wet has low grey mean and low grey variance while a fingerprint that is too dry has high grey mean and low grey variance [56]. An example of three fingerprints with good wetness and dryness, too wet, and too dry is shown in Figure 2.8.

To measure the quality based on the dryness and wetness of the fingerprint, the following strategy was proposed by Wu et al. [56]:

1. Draw the diagram based on mean (x-axis) and variance (y-axis) of the fingerprint pixel intensity values. Note that mean and variance are between

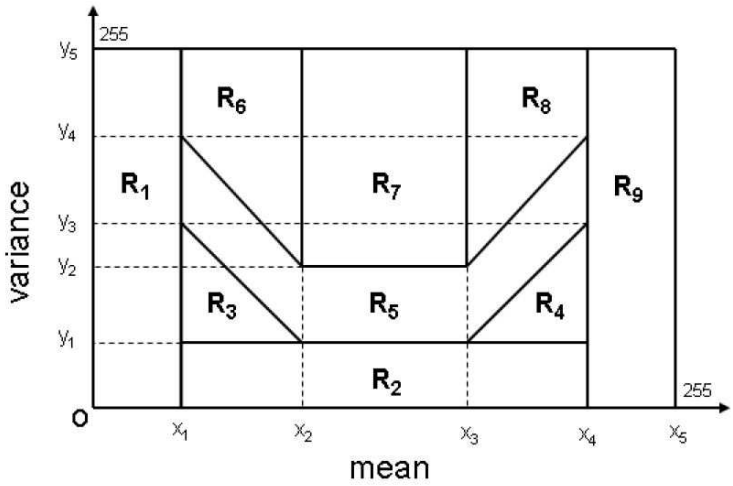


Figure 2.9: Score strategy based mean and variance [56].

zero and 255 (Figure 2.9).

2. Divide the diagram into T regions ($R_1, R_2, ..., R_T$, covering different parts of the diagram), giving each region of the diagram a quality score ($S_1, S_2, ..., S_T$) in such a way that the regions around the centre of the diagram (good dryness and wetness) are assigned with a higher score.

3. If the mean and variance of a region is in the R_i part of the diagram shown in Figure 2.9, the quality score is S_i.

4. The scores of each region and the parameters in Figure 2.9 are set based on the mean and variance of the region as follows:

   $(S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8, S_9) = (0.2, 0.2, 0.3, 0.3, 0.5, 0.8, 1, 0.8, 0.2)$

   $(X_1, X_2, X_3, X_4, X_5) = (0, 80, 120, 220, 230, 255)$

   $(Y_1, Y_2, Y_3, Y_4, Y_5) = (0, 10, 25, 50, 65, 255)$

If the mean and variance of a region are moderate (not too high/low), it is assigned the highest quality score due to the good dryness and wetness; indicated by region R_7 in the above example. For the mean-variance of the other regions, the

closer it is to the region R_7 in the diagram, a higher score is assigned. Likewise, the further away the mean-variance of the region is from the R_7, the lesser score it is assigned to.

2.5.2 Ridge orientation coherence

One of the more powerful measures to estimate the clarity of ridges and valleys in a fingerprint is orientation coherence [14, 54, 55, 57]. Ridge orientation refers to the angle that a ridge crosses through in a small neighbourhood with a horizontal axis. In order to compute the orientation coherence, the image is partitioned into sub-regions of size $b \times b$. For each block B, $g_s = (g_s^x, g_s^y)$ denotes the gradient of grey level intensity at site $s \in B$. The covariance matrix of the gradient vectors of the grey level intensities for all the pixels in the region s is given by [54]:

$$J = \frac{1}{b^2} \sum_{s \in B} g_s g_s^T \equiv \begin{bmatrix} j_{11} & j_{12} \\ j_{21} & j_{22} \end{bmatrix} \tag{2.2}$$

The orientation coherence based on the above symmetric positive matrix is:

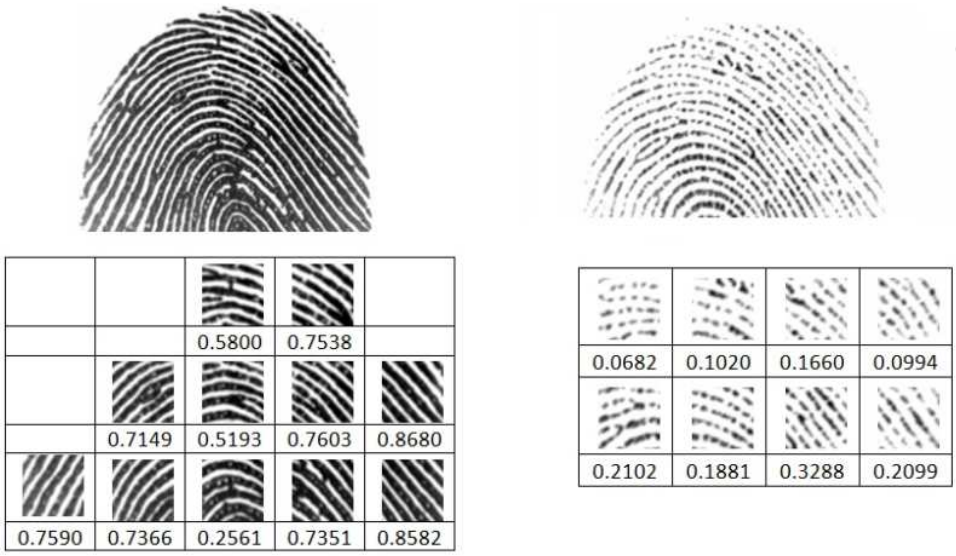
$$\lambda_1 = \frac{1}{2}(trace(J) + \sqrt{trace^2(J) - 4 \times det(J)}) \tag{2.3}$$

$$\lambda_2 = \frac{1}{2}(trace(J) - \sqrt{trace^2(J) - 4 \times det(J)}) \tag{2.4}$$

where $trace(J) = j_{11} + j_{22}$, $det(J) = j_{11} \times j_{22} - j_{12}^2$ and $\lambda_1 \geq \lambda_2$. The normalized Coherence (C) measure is computed as:

$$C = \frac{(\lambda_1 - \lambda_2)^2}{(\lambda_1 + \lambda_2)^2} = \frac{(j_{11} - j_{22})^2 + 4j_{12}^2}{(j_{11} + j_{22})^2} \tag{2.5}$$

In the above equation, $0 \leq C \leq 1$. If the ridges and valleys in the region are distinguished clearly, then $\lambda_1 >> \lambda_2$ resulting in $C \approx 1$. On the other hand, if the



(a) (b)

Figure 2.10: a) a partial fingerprint of good quality and b) poor quality. Orientation coherence metric is shown for each region.

region is of low quality and the ridges and valleys are not clearly separated, $\lambda_1 \approx \lambda_2$ resulting in $C \approx 0$ [54]. In other words, considering that $j_{11} = g_x^2, \quad j_{12} = j_{21} = g_x g_y, \quad and j_{22} = g_y^2$, Equation 2.5 will be one or zero if the values of covariance matrix J are:

$$C = 1, \quad if \quad j_{12}^2 \approx j_{11} \times j_{22}$$

$$C = 0, \quad if \quad j_{12}^2 \ll j_{11} \times j_{22}$$

The regions near the fingerprint singularities are likely to provide more discriminative information than the peripheral regions. However, orientation coherence fails to measure the quality near the singularities (when there is high curvature which result in low coherence) [14]. Figure 2.10 shows the result of computing the orientation coherence on different regions of two good and poor quality fingerprints. In Figure 2.10 (a), the region containing high curvature results in low orientation coherence. In Figure 2.10 (b), the orientation coherence is low for almost all the regions due to the low quality of these regions.

It should be mentioned that the severely distorted regions can be detected by

applying segmentation/masking techniques (e.g. a region of size 10×10 pixels that all the pixel values are identical). Segmentation/Masking techniques can also be used to separate the foreground and background in fingerprints. Two techniques are considered as a basic measure of fingerprint image quality which is done in many fingerprint matching methods.

2.6 Fingerprint Features and Indexing

The pixel intensity values in fingerprint images do not remain the same in subsequent acquisition (Section 1.2) and as a result, it is essential to identify the discriminative characteristics of a fingerprint. These characteristics (or *features*) need to be almost the same for fingerprints of the same finger (considering the changes in fingerprint image pixel intensity in different captures), and at the same time carry discriminative information to distinguish between fingerprints of different fingers. Based on the features, the decision is to be made whether two fingerprints belong to the same finger or different fingers [34, 58].

Three types of information can be detected from fingerprints which are hierarchically categorized into three levels as shown in Figure 2.11. The first level of features known as *level 1* features refers to the overall global ridge flow pattern of fingerprints. The second level of features is known as *level 2/minutiae* features and relates to the fingerprint ridge placement. The third level of features (*level 3* features), refers to the fine ridge details of fingerprints. In next sections, the three level of features are explained in more detail.

2.6.1 Level 1 features (ridge flow pattern)

The global ridge line flow forms a pattern similar to those shown in Figure 2.12 [14]. In general, the ridge lines are locally paralleled, however, they can gradually curve

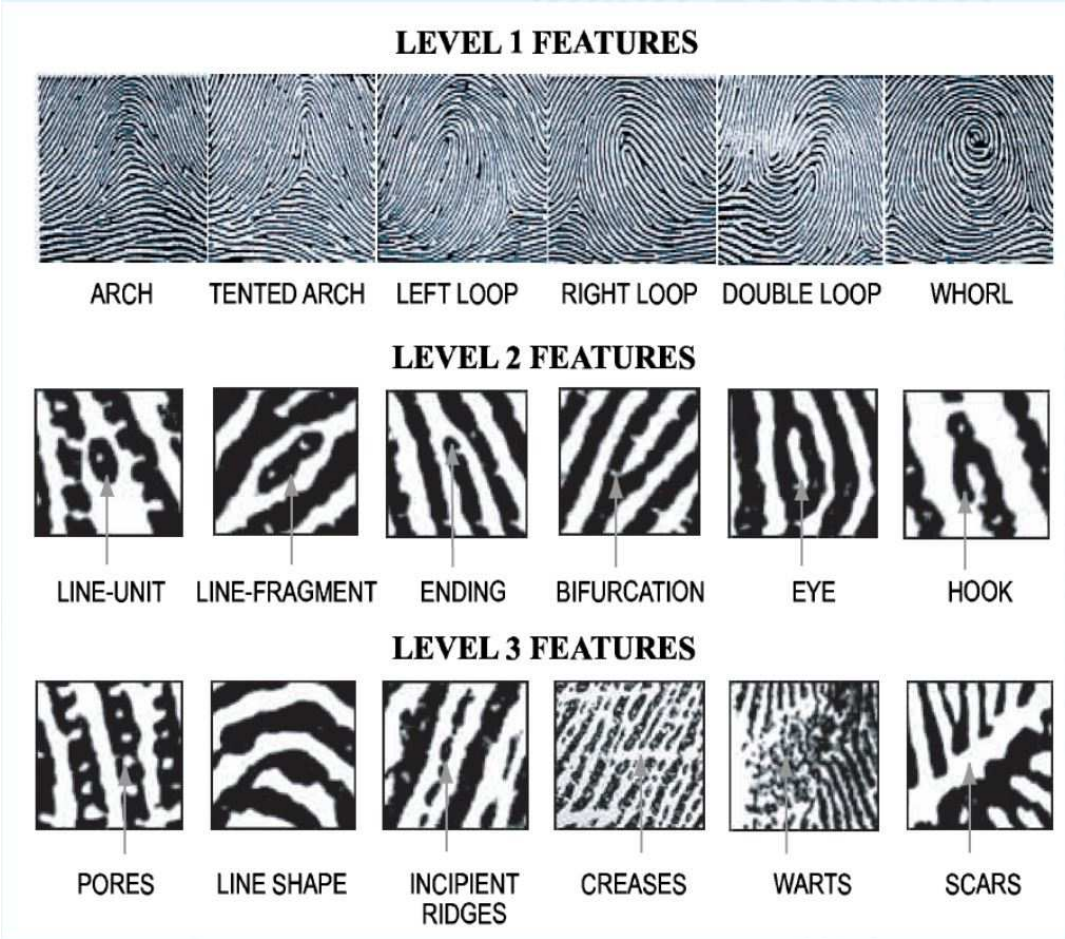
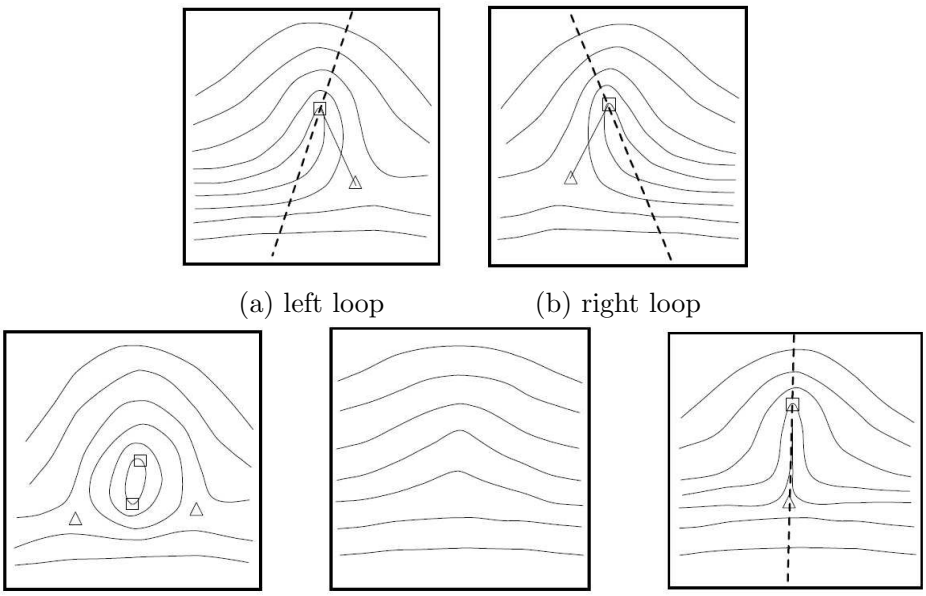


Figure 2.11: Fingerprint features at level 1, level 2, and level 3 [59].

to form certain topological structures [58]. Two known topological structures may exist on the same fingerprint due to the shapes of ridges which are called *singular/reference points*. Singular points are the most important global characteristics of a fingerprint which can be of two types; *Core* and *Triradius/Delta* [60].

A core is defined as *"the north most point of the innermost ridge line"* [14]. However, according to this definition, it is difficult to define the core in fingerprints not having a loop structure (Figure 2.12). Thus, in these cases the core is defined as the maximum point of ridge curvature. In other words, when the fingerprint ridges are turned 180°. Delta is defined as the centre of a triangular region where three different ridge direction flows meet [58, 60, 61] (Figure 1.2 shows an example



(a) left loop (b) right loop

(c) whorl (d) arch (e) tented arch

Figure 2.12: Fingerprint global pattern in a coarse level [14]. Squares and triangles represent the *core-type* and *delta-type* singular points respectively

of core and delta point). Core and delta are complementary to each other and whenever there is a core, there should also be a delta in the fingerprint (can be proved mathematically) [58].

Level 1 features act as control points and are more robust against distortion compared to the level 2 and level 3 features (Section 2.6.2 and 2.6.3). Singular points and coarse ridge lines are useful for fingerprint classification and indexing, but they do not carry enough fingerprint discriminative information that could be used for matching. Therefore, the level 1 features are mainly used for fingerprint classification and indexing (divide fingerprints into roughly 5-6 groups as shown in Figure 2.12).

2.6.2 Level 2 features (ridge placement and minutiae)

At a more local level, a total of 150 different types of ridge characteristic (minutiae details) can be identified [14]. Sir Francis Galton, was the first person who

categorized them and claimed that the minutiae details do not change in a person's lifetime [62]. Most of the minutiae are rarely observed because they are not evenly distributed and they depend heavily on the condition of the impression. Among all of the different minutiae types, the two most prominent ones discussed in the literature are ridge ending and bifurcation [14]. These two minutiae as well as five other minutiae that are often observed, are shown in Figure 2.11. A ridge end is formed when a ridge abruptly ends and a bifurcation is formed when a ridge disjoints into two other ridges (Figure 2.11). The other minutiae types can be described using these two minutiae details. Although minutiae points are widely-used for fingerprint matching, Pankati et al. [30] claimed that extracted information from minutiae details is limited in use for recognition. They emphasized on the need of using non-minutiae based techniques due to the limited information content of the minutiae-based representation.

2.6.2.1 Binarization-based minutiae extraction

Extracting ridge ending and bifurcation can be done by a 3×3 windows after the fingerprint is binarized and thinned. Binarization is the process of converting grey-level images to black and white, based on a defined threshold. If the values in grey colour are higher than the threshold they are changed to "1" (white) otherwise to "0" (black) (Figure 2.13 (b)). Thinning is the process of decreasing the width of ridges to one pixel (Figure 2.13 (c)). After a fingerprint is binarized and thinned, the 9-pixel neighbourhood strategy is applied to extract the minutiae. A 3×3 windows is able to cover every shape of ridge end and bifurcation by being applied on each pixel of the image. If the centre pixel is "0" with "3" zero pixels around it, then it is considered as a bifurcation. If the centre pixel is "0" with only "1" zero pixel around it, then it is called a ridges ending [63] (Figures 2.13 (d) and (e)).

After identifying the minutiae points, they are considered as a set of features

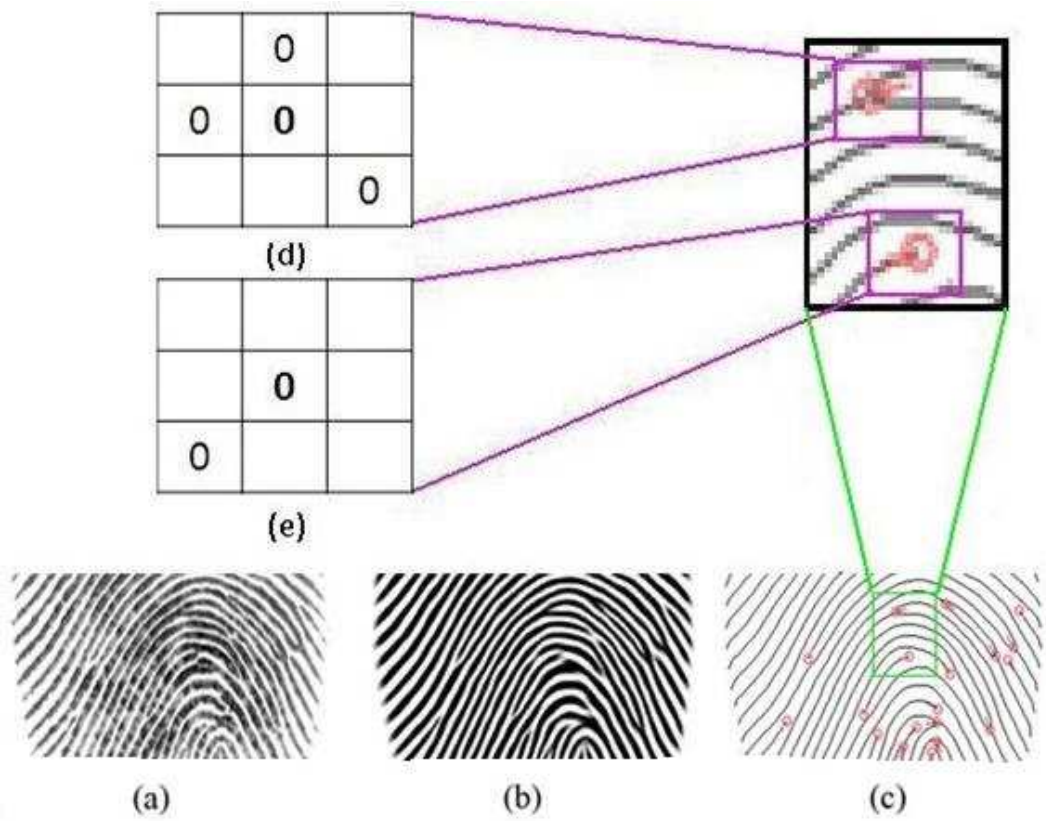


Figure 2.13: a) Original fingerprint, b) Binarized fingerprint, c) Thinned fingerprint, d) Bifurcation on 9-pixel windows, e) Ridge ending on 9-pixel windows.

for the fingerprint. Different algorithms are proposed to define the similarity of these features between two fingerprints. Most of them define a subset for each minutiae point, consisting of its location and orientation.

2.6.3 Level 3 features (fine ridges details)

Level 3 features refer to the fine details of individual ridges that can be detected at a very-fine level. Level 3 features include all dimensional attributes of a ridge, such as ridge path deviation, width, shape, pores, edge contour, incipient ridges, breaks, creases, scars and other permanent details (Figure 2.11). These features are claimed by forensic experts, to be permanent, immutable and unique, and can offer discriminative information for fingerprint recognition [59]. Many researchers are

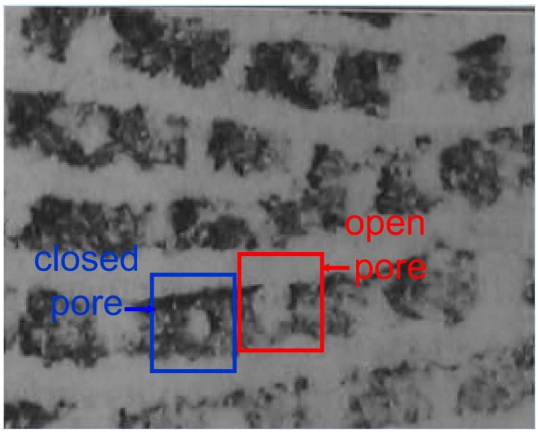


Figure 2.14: An example of the the three level of fingerprint features [64].

working to make use of the level 3 features to increase the matching accuracy [59, 65, 66, 67, 68, 69]. Among all the level-3 features pore/sweat pore attracted more attention as its position and shape are considered highly discriminative and are more available and easily extracted compared to other level-3 features [14]). Figure 2.14 shows the two types of pore extracted from a fingerprint. Depending on the finger pressure on the scanner, it could form a closed/open pore. Closed pore refers to the pores that are fully surrounded by fingerprint ridge and open pores are those that are connected with the valleys and are not fully surrounded by ridges. It has been claimed that $20 - 40$ pores provide sufficient information to recognise a person [14]. However, to accurately detect the sweat pores and other level 3 features, an image with resolution higher than the standard 500 dpi is needed [59, 58]. Many researchers [68, 59, 58] have suggested that the image needs to be at least 1000 dpi resolution for an accurate level 3 feature detection. That is mainly because in low resolution fingerprint images it is infeasible to clearly show these low level features. Figure 2.15 shows an example of a fingerprint image captured from the same finger at 1000 dpi and 500 dpi resolution. Obviously, the fingerprint with 1000 dpi resolution provides more reliable features and level 3 features such as sweat pores and other detailed features are more clearly visible [59, 58, 68].

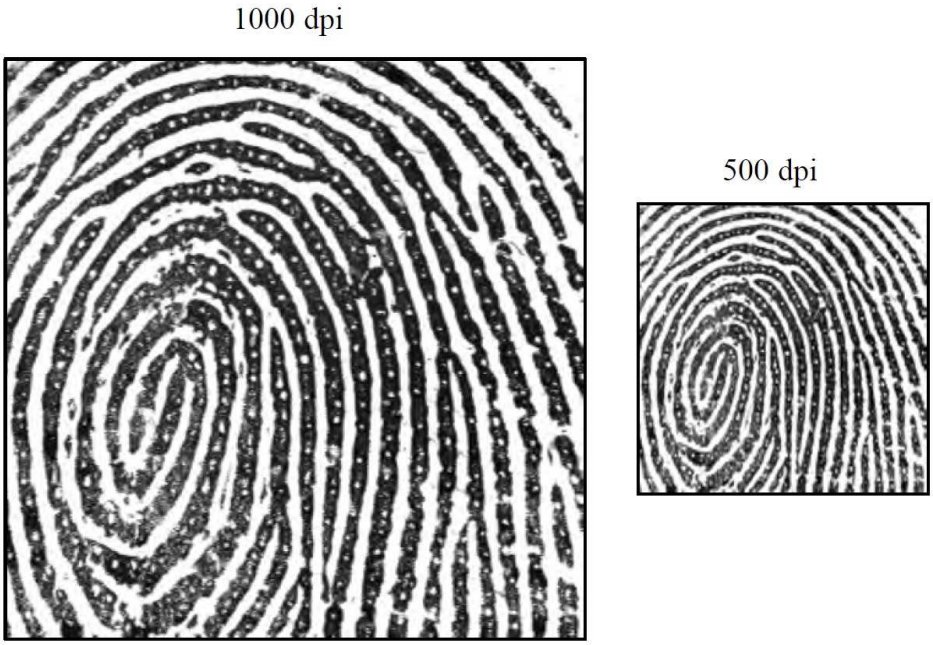


Figure 2.15: The same finger is captured by using a 1000 dpi (on the left) and 500 dpi (on the right) scanner [14].

In the next section, fingerprint matching techniques that use the mentioned features for recognition purpose are explained, followed by the performance metrics used to evaluate the fingerprint identification systems.

2.7 Fingerprint Matching Approaches

Reliable fingerprint matching still remains a challenging issue due to the large variability in fingerprint images from the same finger (large intra-class/within-finger variation). The main reasons for intra-class variation are: rotation, displacement, partial overlap, non-linear distortion, noise, changed skin condition, variable pressure, and feature extraction errors [14] (refer to Section 1.2 for more details). Consequently, fingerprints from the same finger may appear quite different while fingerprints from different fingers may appear similar. For instance, Figure 2.16 shows two intra-fingerprint images (2.16a and 2.16b), that appear to be from two

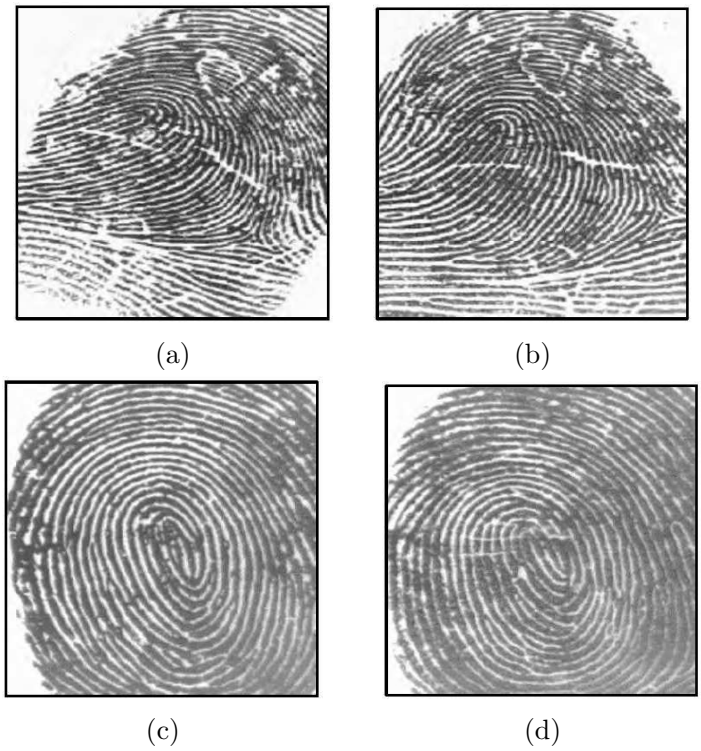


Figure 2.16: a) and b) are two impressions from the same finger that look different to an untrained eye, c) and d) are two impressions from different finger that look quite similar to an untrained eye [14].

different fingers to the untrained eye; whilst Figures 2.16c and 2.16d show two inter-fingerprint images that appear to be similar, even though they are taken from two different fingers,

The intra-class variation and inter-class similarity cause the system to *wrongly* recognise a pair of fingerprints to be a match (from the same finger) or a non-match (from different fingers). These types of wrong decisions are indicated as error rates in the system. The metrics which are used as a benchmark to evaluate the fingerprint matching techniques based on error rates is explained in Section 2.8. The most common-used metric is the Equal Error Rate (EER) which is calculated based on the similarity threshold when both match and non-match ratios are identical. The EER metric is used to evaluate the fingerprint matching techniques that are discussed in the following sub-sections.

Manual fingerprint identification requires a human expert to examine the fingerprints, starting from level 1 features (global structure of the fingerprint, Section 2.6.1) to the lower levels (Section 2.6.2 and Section 2.6.3) [34, 14]. However, Automatic Fingerprint Identification Systems (AFIS) does not necessarily need to follow the same steps. Although the minutiae-based matching techniques are inspired by the manual procedure performed by human experts, there exist other techniques which are designed specially for automatic identification. Most of the techniques proposed in the literature have no difficulty in matching good quality images, however, matching low quality and partial fingerprint remains challenging [34, 14, 40]. Current fingerprint matching techniques can be roughly categorised into three groups: minutiae-based, ridge feature-based (a.k.a. non-minutiae-based), and correlation-based. In minutiae-based methods (Section 2.7.2), minutiae details are extracted from two fingerprints and stored as a set of points in the two dimensional space. Then these methods search to find the alignment between the two fingerprints' set of minutiae points which results in a maximum number of minutiae pairs. In non-minutiae-based methods (Section 2.7.3), other features such as texture information, ridge orientation and etc. of the fingerprint are processed. These methods compare the fingerprints in terms of the features extracted from the ridge pattern. In correlation-based methods (Section 2.7.4), the two fingerprint are spatially correlated to compute the similarity score between them.However, prior to matching, the alignment problem arises. Fingerprint alignment is needed due to the rotation and translation difference between different fingerprints caused by different rotation and displacement of the finger during scanning [70]. By perfectly aligning the fingerprints, the matching could be simplified. The next section discusses the fingerprint alignment as a pre-step to matching followed by the matching approaches.

2.7.1 Fingerprint alignment

One of the intra-class variations is the rotation and/or translation difference between two fingerprints. Even a slight rotation difference between the two images, may result in a wrong matching decision. In other words, an accurate alignment will result in minimizing the false decisions in the system.

In general, there are two types of fingerprint alignment. The first involves aligning the fingerprints based on global features (in level 1 features, Section 2.6.1) whilst the second uses more detailed/local features such as minutiae points (Section 2.6.2) or other lower level features (Sections 2.6.3) [70].

Global alignment methods usually use the fingerprint reference points. As a result, extracting the reference points reliably and accurately is challenging due to the high variation in fingerprints [14]. Also arch type fingerprints (Figure 2.11) do not contain reference points which limits these methods from being applied to all full fingerprints. In addition, partial fingerprints may not be from the fragment of the full fingerprint that contains the reference point(s), regardless of the fingerprint type. Using local features for alignment is more popular, however depending on the local features used, it inherits the advantages and disadvantages of those features (as discussed in the next section) [70]. A robust approach is to perform a relative pre-alignment approach based on the dynamic selection among different alignment techniques (using available/different features) such as superimposing the reference points and computing the correlation of orientation images and other ridge features [70, 71].

The previously developed fingerprint alignment methods, including minutia-based and non-minutia feature based ones, may not be suitable for partial fingerprints [72]. One issue in applying these methods to partial fingerprints is that there could be very few required features on the partial fingerprint. Accordingly, they will either lead to incorrect alignment or not be applicable [72]. For instance,

Khalili et al. have investigated on using fingerprint reference points to rotationally align the fingerprints [73]. However, it is likely that reference points are not available in partial fingerprints. Therefore, it is critical to align the partial fingerprints only based on the available features [21].

The next section discusses the fingerprint matching approaches according to the features extracted in Section 2.6.

2.7.2 Methods based on minutiae (level 2 features)

Let T and Q represent the template and query fingerprint. Minutiae can be extracted by using the technique mentioned in Section 2.6.2 or directly from the grey scale image (refer to [14] for more details). There could be several attributes assigned for each minutiae such as its location, orientation, quality of the fingerprint in the area that minutiae is detected and so on. However, predominantly only the minutiae position (in 2 dimensional space) and orientation is saved in the system as a triplet attribute for each minutiae ($M = \{x, y, \theta\}$) [34]. Therefore, the minutiae set in T and Q can be represented as follows [14]:

$$T = \{M_1, M_2, ...M_m\}, \qquad M_i = \{x_i, y_i, \theta_i\}, \qquad i = 1, 2, ..., m \tag{2.6}$$

$$Q = \{M'_1, M'_2, ...M'_n\}, \qquad M_j = \{x'_j, y'_j, \theta'_j\}, \qquad j = 1, 2, ..., n \tag{2.7}$$

where m and n indicate the number of minutiae in T and Q respectively (m and n do not necessarily need to be identical).

A minutiae in T is considered a match with a minutiae in Q if their spatial distance and directional difference is less than a defined threshold. The tolerance is needed to compensate for the errors in feature extraction and plastic distortion that could change the position of minutiae [14] (refer to Section 1.2 for the errors). Let d and r be the maximum distance and maximum difference between two

minutiae. If the following conditions are met, they are considered a *match*.

$$Distance(M_i, M'_j) = \sqrt{(x_i - x'_j)^2 + (y_i - y'_j)^2} \leq d \tag{2.8}$$

$$DirectionDifference(M_i, M'_j) = min(|\theta_i - \theta'_j|, 360^\circ - |\theta_i - \theta'_j|) < r \tag{2.9}$$

A similarity score between the registered template and query fingerprints needs to be computed now based on the number of matched minutiae points. Let k be the number of matched minutiae between the template and query fingerprint. The similarity score based on k and number of minutiae in both images are computed and normalized by dividing k by the average number of minutiae in both T (m) and Q (n):

$$SimilarityScore = \frac{k}{\frac{n+m}{2}} \tag{2.10}$$

The similarity score can be computed in many different ways. Jea and Govindaraju [21], Srinivasan et al. [74], Jia et al. [75], Feng [76], Lumini and Nanni [77], proposed different ways to compute the similarity score in such a way that the rule and parameters are optimized to best separate inter and intra fingerprints. Most of these techniques need a separate training set to adopt the parameters which may not be applicable in many cases [14]. In Equation 2.10, depending on the similarity score, the system can decide whether Q and T belong to the same finger or not.

However, Maltoni et al. and Pankanti et al. (in [14] and [30] respectively), mentioned three main reasons that induce designers to look for additional fingerprint distinguishing features beyond minutiae. First, additional features may be used in cooperation with minutiae (not as an alternative) to increase system accuracy and robustness. It should be mentioned that several non-minutiae feature based techniques use minutiae for pre-alignment or to define anchor points.

Second, reliably extracting minutiae from poor quality fingerprints is difficult. Although minutiae may carry fingerprint discriminatory information, they do not always constitute the best trade off between accuracy and robustness for the poor quality fingerprints. Third, non-minutiae-based methods may perform better than minutiae-based methods when the fingerprint sensor area is small. In fingerprints with a small area, only 4-5 minutiae may exist which do not provide enough discriminative information if the sample population is large [30].

Minutiae based algorithms works well on high quality images, but they all suffer from detecting spurious minutiae especially in low quality images. The reason for this is that minutiae are defined as the points that a ridge ends or disjoints. Although there is not an objective measurement of the quality of a fingerprint (Section 2.4), practically, it refers to the clarity of ridges and valleys in the fingerprint image [78]. Thus, minutiae extraction in low quality images will lead to the detection of false minutiae due to unclear ridges and valleys. One of the methods that researchers use to solve this problem is to extract the minutiae from valid and not distorted regions of the fingerprint. But the problem remains unsolved if no (or very few) valid regions are available on the fingerprint.

The other problem in minutiae-based algorithm is that they work only on the limited information available on the fingerprint. The extracted information in minutiae based methods are limited and algorithm developers should explore the use of non-minutiae based information of the fingerprint. The limitation in minutiae-based methods is that only properties of some points of the ridges are used (i.e. the end of the ridge when there is a termination, Section 2.6.2) and the rest is unused.

The problem of working on the limited information of the fingerprint affects the system performance even more so when dealing with partial fingerprints. Since partial fingerprints have already lost some potential information compared to a full

fingerprint, the minutiae-based methods use some of the remaining information. Typically, due to the few number of available minutiae points, minutiae based algorithms will not work satisfactorily [34].

In addition, in some minutiae-based approaches, a minutiae matching technique is applied as 2-D point matching to determine the global alignment of the fingerprints, leading to an optimal minutiae matching. This is done by searching for possible combinations of minutiae pairs which is found difficult in most global matching techniques. As mentioned in Section 1.2, non-linear distortion is caused due to the finger skin elasticity and it has a significant effect on the fingerprint features. For instance, the higher non-linear distortion leads to higher difference in two identical minutiae point in two intra-fingerprints. In addition, treating the fingerprint images globally increases the search space and complexity of finding the minutiae pairs. Therefore, most of the global minutiae methods are neither efficient nor robust in the presence of non-linear distortion of the fingerprint [14].

Recently researchers tried to solve these problems by introducing local minutiae matching. Local minutiae matching methods use the attributes which are invariant with respect to global transformation (e.g. translation) and therefore fingerprints can be matched regardless of alignment. On the other hand, local minutiae matching techniques loses the global relationship of the fingerprint and therefore the discriminative information to distinguish imposter matches is reduced [79].

Win and Sein in 2011, [80] proposed a method which is specially designed for low quality images based on computing the correlation of the fingerprint images. The following is their comment about the performance of correlation-based methods as compared to minutiae based methods: *Generally, fingerprint identification approaches are minutiae-based and correlation-based. Although the minutiae-based method is popular and extensively used method for fingerprint identification, it shows poor performance for low quality images.*

Tico and Kuosmanen [81] proposed their minutiae method of fingerprint matching based on the orientation field (the angle a minutia makes with respect to the horizontal axis) of the fingerprint minutiae. In their work, first, minutiae points are extracted followed by computing the orientation field of the minutiae. The matching score of two fingerprints is computed based on the similarity of the orientation field of the common minutiae points in two fingerprints. A match or non-match decision is made based on the similarity score between two fingerprints.

Gao et al. [82] proposed a method based on fingerprint ridge ending and bifurcation for fingerprint recognition. In their method, a graph is drawn out of the minutiae points and the neighbourhood of each minutiae is identified. For each minutiae, the neighbouring minutiae are projected onto a circle with a constant diameter. For each neighbouring minutiae, the elongation of the distance caused due to the projection and the angle with the x-axis are used as new sets of parameters to represent the neighbourhood of the selected centre minutiae. In order to make the vectors invariant to the rotation and translation, the values are normalized. A feature vector of a given fingerprint consist of normalized vectors for each minutiae. In order to compare a query fingerprint (Q) with a template fingerprint (T), corresponding minutiae in Q and T are identified by comparing each vector corresponding to each minutiae in Q with each vector corresponding to each minutia in T. This is done by counting scores when the angle and elongation differences are below a predefined threshold value. After identifying the corresponding minutiae, the matching score is calculated using the number of minutiae pairs matched. When the score is above a given threshold, the finger prints are considered matched.

Vijayaprasad et al. [38] and Jea and Govindaraju [21] proposed two methods for *partial fingerprint matching* based on the minutiae features. In the following (Section 2.7.2.1) these two methods are discussed followed by a summery of

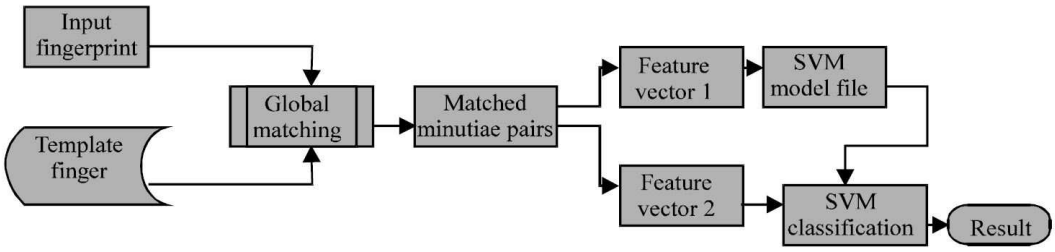


Figure 2.17: Proposed SVM architecture by Vijayaprasad [38].

minutiae-based fingerprint matching methods.

2.7.2.1 Partial fingerprint matching

Vijayaprasad et al. [38]:

Vijayaprasad et al. in 2010, presented a new minutiae-based partial fingerprint matching using Support Vector Machine (SVM). They have designed an SVM architecture to classify the partial fingerprints with different sizes (Figure 2.17). The input (query) and template (registered) fingerprints are initially matched according to their minutiae points as follows [38]:

Step 1

Sort the minutiae from query and registered fingerprints according to their radial angle and radial distance.

Step 2

Set a reference minutiae point (with coordinates (x, y, θ)) and for all other minutiae, convert their properties to a polar coordinate system as:

$$\begin{pmatrix} r_i \\ a_i \\ \theta_i \end{pmatrix} = \begin{pmatrix} \sqrt{(x_i - x)^2 + (y_i - y)^2} \\ tan^{-1}(\frac{y_i - y}{x_i - x}) \\ \theta_i - \theta \end{pmatrix} \tag{2.11}$$

where (x_i, y_i, θ_i) is the coordinates of the minutiae points and (r_i, a_i, θ_i) is

the polar coordinate system. r_i, a_i, and θ_i are radial distance, radial angle, and orientation of minutiae with respect to reference minutiae respectively.

Step 3

Find the same type (ridge ending/bifurcation) of minutiae for each set and calculate the following:

- $Radialdistance = 1/L(\sum |r_i - r_j|)$
- $Radialangle = 1/L(\sum |a_i - a_j|)$
- $Minutiaedirection = 1/L(\sum |\theta_i - \theta_j|)$

where i and j are the indices of the two minutiae that are compared and L is the number of recorded same type of minutiae (ridge ending/bifurcation) for each fingerprint and $0 \leq i \leq L$

Step 4

Similarity score of two minutiae set is computed by summing the radial distance, angle and direction computed above.

Step 5

Set the threshold (ε), if the similarity score of the *two minutiae point* is greater than the threshold, they are considered as matched.

Step 6

Calculate the matching score of two fingerprints as:

$$MatchScore = \frac{m^2}{M_Q \times M_R} \tag{2.12}$$

where m is the number of matched minutiae and M_Q and M_R are the total number of minutiae in query and registered fingerprints respectively.

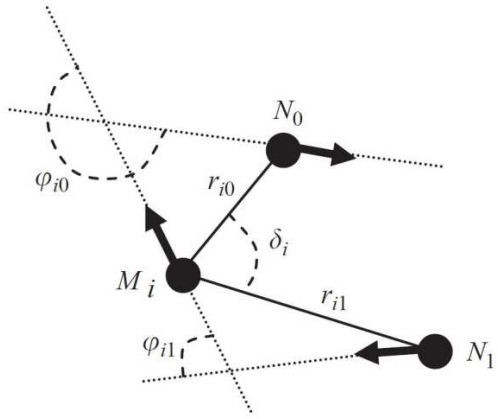


Figure 2.18: Information of the minutiae M_i and its two nearest neighbours N_0 and N_1 to generate the secondary features [21].

Step 7

Record the maximum number of matched minutiae.

Two feature vectors are constructed according to the matched minutiae. Feature vector 1 consists of the direction and angle between the matched points and feature vector 2 consists of the 4-tuple of (x, y, θ, φ) where x and y are the relative positions, θ represents the angle and φ is the invariant moments computed for the Region of Interest (ROI) [83, 84]. A matching score is calculated for the intra and inter fingerprints. The SVM classifier is then trained by the two feature vectors obtained from inter and intra comparisons of different classes (fingers).

Jea and Govindaraju [21]:

Jea and Govindaraju proposed a minutiae-based partial fingerprint matching that extracts secondary features from minutiae information. A flow based network matching was proposed to match a one-to-one correspondence between the secondary features and minimize the total feature distance between query and registered fingerprints. If in $(M_i) = (x_i, y_i, \theta_i)$, x_i and y_i are the coordinates and θ_i is the orientation; and $N_0 = (x_{n0}, y_{n0}, \theta_{n0})$ and $N_1 = (x_{n1}, y_{n1}, \theta_{n1})$ are the two nearest-neighbours of the minutiae M_i, the secondary feature is a 5-tuplet of $(M_i) = (r_{i0}, r_{i1}, \varphi_{i0}, \varphi_{i1}, \delta_i)$ where r_{i0}, r_{i1}, φ_{i0}, and φ_{i1} are the euclidean distance

Table 2.2: Comparison of the performance of Vijayaprasad [38] and Jea [21] methods with different sizes at random positions on dataset FVC2002_DB1 in terms of the metrics TER and EER (Section 2.8).

(%)	TER (%)		EER (%)
Image size	Vijayaprasad [38]	Jea [21]	Jea [21]
10	-	60.87	38.21
20	-	29.24	17.11
30	-	17.73	9.12
40	10.4	1.36	5.25
50	5.77	5.98	3.17
60	4.95	5.03	2.52
70	3.25	3.41	1.77
80	2.70	2.89	1.74
90	2.59	2.93	1.71

and orientation difference between minutiae M_i and its neighbours N_0 and N_1 respectively. δ_i represents the acute angle between the line segments the M_iN_0 and M_iN_1 as demonstrated in Figure 2.18.

The similarity score between registered and query fingerprint is defined according to the number of matched minutiae, number of minutiae points on overlapping area and average feature distance. The same as Vijayaprasad et al.'s method [38], a different percentage of the fingerprint foreground area was used to evaluate the performance of their method. Table 2.2 shows the experimental result of these two methods which is conducted on the FVC 2002_DB1 dataset and compared with the proposed partial fingerprint identification method in Chapter 5.

As mentioned in Section 1.2.4, most of the issues in partial fingerprint matching are the same as full fingerprint matching. However, due to the partial information availability and high chance of image degradation, partial fingerprint matching has its own special requirements. The issues in minutiae-based methods which were discussed in this section which need to be considered in partial fingerprint matching can be concluded as the following:

- Difficulty in reliably extracting minutiae from poor quality fingerprints.

- The need for additional features (than minutiae) to improve accuracy.
- The possibility of non-minutiae features performing better than minutiae in partial fingerprinting.
- Detecting spurious minutiae in low quality fingerprints.
- Working only on limited information available in the given fingerprint.
- Global minutiae matching are neither robust nor efficient in handling non-linear distortion.

2.7.3 Ridge feature-based matching technique

Fingerprint matching techniques using any kind of fingerprint features other than minutiae points grouped as ridge-feature based matching. Correlation-based technique (Section 2.7.4) as an image-based technique are considered as a subcategory of the ridge-based matching technique. The most commonly used non-minutiae fingerprint features are [14, 85, 86]:

- Size of the fingerprint and shape of the external fingerprint silhouette.
- Number, type, and position of singular points.
- Global and local texture information.
- Geometrical attributes and spatial relationship of the ridge lines.
- Level 3 features (e.g., sweat pores).
- Other features: fractal features ([87]), shape features derived from the one-dimensional projection of the two dimensional fingerprint image ([88, 89, 90]).

The fingerprint features used in this group of methods vary a lot but *depending on the utilised feature* they may suffer from low discriminative capability of

the features (i.e. Qader et al.'s approach [91]) [14, 31]. Low discriminative capability relates to the fact that these features will not sufficiently distinguish one fingerprint from another. For instance, fingerprint singular points cannot reveal high discriminative information between different fingerprints. On the other hand, methods in this category are not limited to working only on the limited information of the fingerprint and have the potential of revealing more discriminative information than minutiae-based methods.

2.7.3.1 Texture feature-based technique

Global and local texture information are one of the most commonly used features in ridge-based feature matching techniques, which are utilised as an alternative or complement to minutiae features [40]. An image texture refers to a set of metrics to quantify the texture of an image and gives information about the spatial characteristic (intensity, color, etc) of an image or part of an image [92]. As stated by Jahne [92], analysing texture information provides the ability to describe and differentiate complex patterns. In relation to fingerprinting, the fingerprint images are a spatial repetition of basic elements which are characterized by their properties such as: scale, orientation, frequency, symmetry, isotropy, and so on [40]. Except the singular points, fingerprints can be defined as smooth ridge orientation and frequency [40].

Ito et al. [93] proposed a method based on phase component of the fingerprint. Their method consists of three main steps. First is alignment: different rotation of the query fingerprint is stored in the system and the registered fingerprint is compared with the query fingerprint (rotated in different angles). Second step is common region extraction: this step is done to improve the accuracy of matching as matching two overlapping regions is more accurate than non-overlapping regions. To extract the common regions in two fingerprints, the x-axis and y-axis of the

pixel projection is examined and common effective areas of two images are accepted for matching. The third step is computing the similarity of fingerprints based on the phase correlation of fingerprint images.

When their method was compared with minutiae-based method, it showed better performance in terms of EER. The EER of their method and a minutiae-based method are *1.9%* and *4.81%* respectively on a private dataset they collected [93]. But the main limitation of their work is that the similarity is computed globally and it may not work well when the non-linear distortion in fingerprint is high. The other problem is that finding common regions based on a pixel projection is not very accurate and the resulting images may not cover the actual common area when there is distortion even in one of the images.

Yang et al. [83] proposed a method based on extracting invariant moments of the fingerprint. Invariant moments was first introduced by Hu [84]. Hu proved that his seven moments are invariant to RTS (Rotation, Translation, and Scaling). These moments are widely used in pattern recognition. Yang et al applied these moments in fingerprint matching. In their method, first the core point of the fingerprint needs to be located. A window with the size of 64×64 around the core point is cropped from the fingerprint. The invariant moments of the cropped region are computed and match/non-match decision is made based on the distance between the extracted moments of the two fingerprints.

Although their method is invariant to RTS and is efficient, there are some limitations in their work. First, their method is dependent on detecting the core point. There is no guarantee that the core point is available in a partial fingerprint and if it is, the quality of the fingerprint may be better in other regions than around the core point. The other problem is that they use a small region of the fingerprint while the rest of the information remains unused. To extract the common region in both fingerprints, a rectangle around the core point is cropped.

However, fingerprints need to be aligned first to identify the same region in both. With regards to this, there are two issues in their method. First, doing so they do not take advantage of invariant moments completely. Second, the algorithm is dependent on the precise location of the core point to extract the common region of two fingerprints. Precise detection of the core point in two impressions of the same finger is difficult due to the intra-class variation. The next problem is that they used 50% of the data set as training set, but they have used all the data set (including the training set) to evaluate their method. This will directly affect the performance of the system and lead to a lower EER compared to evaluating the system only on the test set.

In 2007, Qader et al. [91] proposed a fingerprint matching based on Zernike moments (ZMs) [94]. These moments are also invariant to RTS like Hu moments and the steps in their approach are very similar to the steps in Yang et al.'s approach. The fingerprint is enhanced and a window around the core point of the fingerprint is cropped. The Zernike moments are extracted from the cropped region and Euclidean distance of the template and query fingerprint feature set is computed. Based on the computed Euclidean distance they decide that two fingerprints are different impression of the same finger or not. They evaluated their experiment on the FVC 2002 dataset [95], and they selected *6* out of *8* impressions of each finger while 50% of the selected impressions are used for training and the rest for testing. Their approach suffers from the same problems as that of Yang et al.'s [83].

Despite the above discussion on Ito et al.'s, Yang et al.'s, and Qader et al.'s methods, the general properties of non-minutiae-based methods can be concluded as follows: Non-minutiae-based methods are not restricted to work on limited information of a fingerprint (like minutiae-based approaches), and can make use of more reliable features than minutiae. However, this does not guarantee that every

extracted feature has a high discriminative capability and feature selection remains a difficult task in this group. Using the suitable features, the performance of the algorithm in this group can compete with methods in other groups. The importance of these group of feature is their potential in providing high discriminative information which could be very useful in terms of partial fingerprint matching that needs to make the best out of the available fingerprint information.

2.7.3.2 Level 3 feature-based technique

As discussed in Section 2.6.3, level 3 features are permanent and unique, and reveals high discriminative information of the fingerprint. Considering these properties, using level 3 features in partial fingerprint matching (if available) is essential. Although extracting level 3 features requires high quality image resolution (at least 1000 dpi), recently researchers are motivated to make use of these features. Among the level 3 features, researchers have investigated more on *pore/sweat pore* as its position and shape are considered highly discriminative compared to other level 3 features [67].

Stosz and Alyea [96] proposed a method whereby images were taken by a fingerprint scanner with the surface resulting in images with a size of 640×480 pixels with and resolution of approximately 2400 dpi and 1270 dpi in horizontal and vertical directions respectively. In the enrolment process, the singular point, level 2 features (Section 2.6.2), and the regions containing pores are selected manually and stored in the system. A similarity score is assigned to the fingerprints *"T"* and *"Q"* based on the number of common regions/segments of two fingerprints (S_S) as well as a similarity score based on minutiae type, location, and orientation (S_M). Also, another similarity score (S_P) is assigned to the fingerprints based on the pore locations. The flowchart of their multi-level verification is shown in Figure 2.19. The fingerprints need to have the minimum number of common

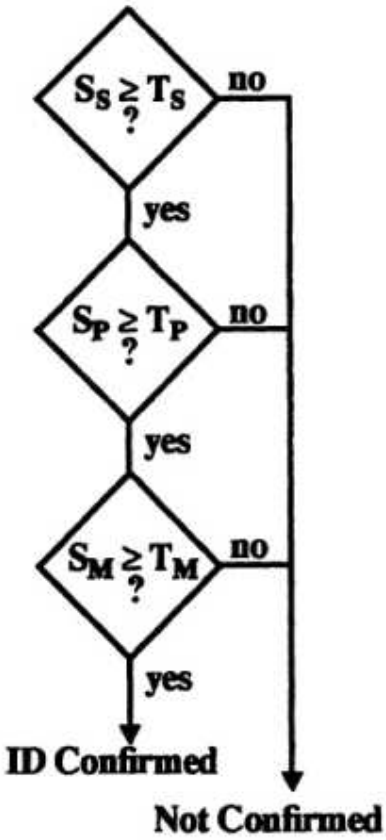


Figure 2.19: Multi-level verification process proposed by Stosz and Alyea [96].

regions to to be eligible for further comparisons ($S_S \geq T_S$, T_S is the threshold for minimum common regions).

If two fingerprints pass the first step, they are examined based on their similarity score on pore location ($S_P \geq T_P$, T_P is the threshold for similarity score on pore location). If the two fingerprints pass this level as well, they will be compared based on the similarity score assigned to them according to their minutiae type, location and orientation ($S_M \geq T_M$, T_M is the threshold for the similarity of minutiae points). If in any level of the verification processes, the two fingerprints cannot pass the hurdle in that step, they are considered as a non-match. The experimental results performed by the authors showed that the error rate significantly reduces with using information extracted from pores along with the level 2

features, compared to only using level 2 features. Later Roddy and Stosz used statistical analysis on pores to measure its effect on fingerprint identification system performance [97]. They focused on the improvement that could be achieved by using fingerprint pore information in addition to minutiae points.

2.7.4 Correlation-based techniques

Correlation-based techniques measure the similarity of two fingerprints based on their spatial correlation. Methods that use this technique can be considered as a sub-family of non-minutiae methods (Section 2.7.3). Correlation-based methods compare the two images pixel-wise to identify how strongly they are co-related [98]. Correlation coefficients range from *-1* to *+1*; the closer it is to *+1* the more related the two images are. The correlation between two signals (cross-correlation) is a standard approach to find out how the two signals are related. It can be thought of as the function of the relative time between signals [98]. Mathematically, the cross-correlation of two discrete functions can be represented as follows:

$$(f \bigotimes g) = \sum_{i=0}^{N-1} (f_i \times g_i) \tag{2.13}$$

Where i represents the signal value whose value ranges as $i = 0, \ldots, N-1$; up to the size of the signal length (N).

To apply the cross-correlation to images, the brightness of the image pixels needs to be fixed; otherwise it would affect the matching. These conditions in images may cause different values of mean and variance on the fingerprint images. To bring them to the desired mean and variance (M_0 and Var_0), the following computation needs to be done [98]:

$$Q'(i,j) = \begin{cases} M_0 + \sqrt{\frac{Var_0(Q(i,j)-M)^2}{Var}} & \text{if } Q(i,j) \geq M_0 \\ M_0 - \sqrt{\frac{Var_0(Q(i,j)-M)^2}{Var}} & \text{otherwise} \end{cases} \tag{2.14}$$

Where, $Q(i,j)$ indicates the grey-level value at pixel (i,j) and $Q'(i,j)$ indicates the normalized grey-level value at pixel (i,j). After normalizing the image pixels, the normalized cross-correlation in 2 dimensional space of two images can be computed as follows [99]:

$$NCC = \sum_{x,y} \frac{(Q(x,y) - \bar{Q})(T(x,y) - \bar{T})}{\delta_Q \times \delta_T} \tag{2.15}$$

Where $\bar{T}$ is the mean of the template fingerprint pixel values, and $\bar{Q}$ is the mean of query fingerprint Q. δ_T and δ_Q are the standard deviation of fingerprint T and Q respectively. Like non-minutiae based methods, correlation-based methods compute the similarity of two images and if the similarity score of two images is higher than the defined threshold, the query fingerprint will be accepted as genuine otherwise it will be rejected.

To overcome the issue of translational difference between the two fingerprints, NCC can be computed for all the possible overlaps of the two images. Figures 2.20 (a) and (b) show registered and query sample images with the size of 6×6 and 3×4 pixels respectively. In this case, there are 12 possible overlap between these two images where all the pixels in both images are considered and the NCC values of these overlaps are shown in Figure 2.20 (c). The red and blue rectangles in Figure 2.20 (d) show two possible positions of overlapping Figures 2.20 (a) on Figures 2.20 (b). The red and blue rectangles in Figure 2.20 (e) show their corresponding NCC values. When the pixels of both images are identical, the NCC value is 1. This technique is knows as the sliding window technique which is widely used when applying NCC in image registration applications.

	1	2	3	4	5	6
1	1	0	0	1	0	1
2	0	0	0	1	0	0
3	0	1	1	0	1	1
4	1	0	0	0	0	1
5	1	0	1	0	1	0
6	1	1	0	0	0	0

(a)

	1	2	3
1	1	0	1
2	0	0	0
3	1	0	1
4	0	0	0

(b)

	1	2	3	4
1	0.2500	0.2500	0.2500	0.3536
2	-0.2390	-0.1250	-0.5976	0.1195
3	0.2390	-0.1250	1	-0.1250

(c)

	1	2	3	4	5	6
1	1	0	0	1	0	1
2	0	0	0	1	0	0
3	0	1	1	0	1	1
4	1	0	0	0	0	1
5	1	0	1	0	1	0
6	1	1	0	0	0	0

(d)

	1	2	3	4
1	0.2500	0.2500	0.2500	0.3536
2	-0.2390	-0.1250	-0.5976	0.1195
3	0.2390	-0.1250	1	-0.1250

(e)

Figure 2.20: Profiles of a fingerprint characteristic of an imposter and a genuine user. If the matching score of two fingerprints is higher than a pre-defined threshold, it is considered a match [100]

One of the recent approaches based on normalized cross-correlation is proposed by Karna et al. [98]. Their method consists of three steps. The first step is to align the fingerprint to make it invariant to rotation and scale. The second step is to extract the common region in both fingerprints which is performed the same as the common region extraction in Ito et al.'s method. The last step is to compute the correlation of the extracted region and record the highest correlation score as the similarity score of the two fingerprints (as shown in Figure 2.20). At the end if the score is higher than the defined threshold they are accepted as genuine, otherwise rejected as imposter. There are some limitations in this method. First of all, the alignment process (with regards to rotation and translation variance) is done manually by selecting two points in each of the template and query fingerprints. This will help the algorithm for a very accurate alignment in genuine matches but it is not possible to do the alignment like this in large populations. In addition,

aligning two fingerprints manually have a direct effect on the algorithm's accuracy for the methods that are not invariant to RTS. The rest of the problems in this method are the same as Ito et al.'s method [93]. To extract common regions in both fingerprints they have used the same method as Ito et al. If the extracted common region is not accurate, it will directly affect the accuracy of matching. The last problem relates to the non-linear distortion. Even if the extracted region is accurate but the similarity measurement is not applied locally, the matching result will not be very accurate due to the non-linear distortion. To evaluate their method, it performs better than minutiae-based methods in terms of EER. The EER of their method is around 2% while the minutiae-based method's EER is around 3% (the experiment was conducted on a private data set) [98].

In the next section, a comparative study of different region-based similarity measurements (correlation-based metrics) that are widely used for object recognition are introduced and discussed.

2.7.4.1 Correlation-based Similarity Measurements

One of the major approaches for fingerprint recognition (instead of working on minutiae points) is region-based approach. To measure the similarity of fingerprints in a region-based manner different correlation-based metrics are available which work on fingerprint regions in a pixel-by-pixel manner. Cross correlation is a standard approach for feature extraction as well as being an important element of more sophisticated techniques [101, 99]. Correlation techniques (as an important category of fingerprint matching approaches) have attracted many researchers to propose matching techniques [102, 98, 31]. However, a comprehensive study of different correlation-based techniques in a special case such as fingerprint matching is missing in the literature.

The information provided by one pixel is insufficient to perform a reliable

Table 2.3: Region-based matching measurements. In all cases f and t represents the two images to be compared.

SIMILARITY MEASURE	FORMULA
Sum of Absolute Differences (SAD)	$\sum_{x,y} \lvert(f(x,y) - t(x,y)\rvert$
Sum of Squared Differences (SSD)	$\sum_{x,y} (f(x,y) - t(x,y))^2$
Zero-mean Sum of Absolute Differences (ZSAD)	$\sum_{x,y} \left\lvert(f(x,y) - \bar{f}) - (t(x,y) - \bar{t})\right\rvert$
Zero-mean Sum of Squared Differences (ZSSD)	$\sum_{x,y}((f(x,y) - \bar{f}) - (t(x,y) - \bar{t}))^2$
Locally scaled Sum of Absolute Differences (LSAD)	$\sum_{x,y} \left\lvert(f(x,y) - \frac{\bar{f}}{\bar{t}} t(x,y)\right\rvert$
Locally scaled Sum of Squared Differences (LSSD)	$\sum_{x,y} (f(x,y) - \frac{\bar{f}}{\bar{t}} t(x,y))^2$
Sum of Hamming Distances (SHD)	$\sum_{x,y} (f(x,y)\ bitwiseXOR\ t(x,y))$
Normalized Cross Correlation (NCC)	$\frac{1}{n} \sum_{x,y} \frac{(f(x,y)-\bar{f})(t(x,y)-\bar{t})}{\sigma_f \sigma_t}$

matching. Therefore, the pixel becomes the centre of a regularly sized window and will be compared with a similarly sized region of the other image. Matching measures are used to provide a computational measure of likeliness by taking two regions and finding the similar/same pixels within the other region, while moving along the corresponding region (all possible portions of the other sub-region) [103].

A comparative study is conducted on eight correlation-based similarity measurements. These measurements are listed in Table 2.3 which are introduced in [103, 104, 105]. If the matching score of two images is low in NCC (or high in SAD, ZSAD, etc) it will be considered that the two images do not match with a high degree of confidence (i.e. are not *similar*).

The Sum of Absolute Differences (SAD) and the Sum of Squared Differences (SSD) of the two images are intuitively the simplest and computationally the least expensive metrics. In SAD the pixel values of the two regions are subtracted followed by summing the absolute value of subtraction whilst SSD aggregates the

squared differences of pixel values in the two regions. SAD and SSD return a value of zero if the two images to be compared are exactly identical. However, if there is a constant offset between pixel intensities, these two measures do not return the correct result (zero). This problem is solved via the Zero mean Sum of Absolute Differences (ZSAD) and the Zero mean Sum of Squared Differences (ZSSD) by subtracting the mean value of the matching area from each pixel intensity. However, another unsolved issue would be when the pixels intensities in one image are equivalent to the intensities of the other image multiplied by a gain factor [103, 106, 107]. Locally scaled Sum of Absolute Differences (LSAD) and Locally scaled Sum of Squared Differences (LSSD) overcome this issue. In these two measure, the second image is multiplied to the average of pixel intensity values of image one divided by the average pixel intensity values of image two before subtracting them. However, when there is a constant offset between two images they fail.

Normalized Cross Correlation (NCC) is more robust and complex than both SAD and SSD under uniform illumination changes as it involves numerous multiplication, division and square root operations so it has been widely used in image matching, object recognition and industrial inspection [108]. However, NCC overcomes both of the mentioned issues of SAD, SSD, ZSAD and ZSSD by subtracting the mean from pixel intensities and dividing it by the standard deviation of the matching area (normalization within the window which compensates differences in gain and bias [108, 109]). NCC is statistically the optimal method for compensating Gaussian noise [110, 111] which ranges from -1 to $+1$ where -1 and $+1$ represent a reverse match and a perfect match respectively.

Figure 2.21 shows three different cases that illustrates the above mentioned problems. In case 1, both of the image pixel values are identical and all the metrics correctly indicate that. In case 2, pixel values of one of the images are

Case 1:			
$F_{(x,y)}$		$t_{(x,y)}$	
1	2	1	2
1	2	1	2

Case 2:			
$f_{(x,y)}$		$t_{(x,y)} = f_{(x,y)} + 2$	
1	2	4	5
1	2	4	5

Case 3:			
$f_{(x,y)}$		$t = f_{(x,y)} \times 3$	
1	2	3	6
1	2	3	6

	Case 1	Case 2	Case 3
$SAD_{(f,t)}$	0	12	12
$ZSAD_{(f,t)}$	0	0	4
$LSAD_{(f,t)}$	0	1.3333	0
$SSD_{(f,t)}$	0	36	40
$ZSSD_{(f,t)}$	0	0	4
$LSSD_{(f,t)}$	0	0.4444	0
$NCC_{(f,t)}$	1	1	1

Figure 2.21: Illustrating the problem of the correlation metrics with constant offset (Case 2) and multiplication factor (Case 3). In each case, f and t represent the two images to be compared.

added by 3 (constant offset between pixel values). As discussed, SAD and SSD fail to show these two images are identical (regardless of the constant offset) but ZSAD and ZSSD correctly return zero. In case 3, pixel values of the second image are multiplication of the pixel values in the first image by 3 (multiplication factor). In this case SAD, SSD, ZSAD, and ZSSD fail but LSAD, LSSD, and NCC correctly show that these two images are identical (regardless of the multiplication factor). However, as shown, LSAD and LSSD both fail in case 2 and NCC is the most reliable metric to solve the problems of constant offset and multiplication factor due to its above mentioned characteristics.

Table 2.4 shows the EER (Section 2.8) of applying the aforementioned correlation-based similarity measurements on the dataset FVC2002_DB1. The aim of this section is to provide a comparison of correlation measurements to know which one works better on fingerprint recognition. In order to combine the local similarities and compute the final similarity of the fingerprints, local similarities are averaged (arithmetic mean) with no further processing as in Chapter 4. As mentioned, NCC

Table 2.4: EER(%) of different correlation-based similarity measurements on part of the FVC2002_DB1 dataset.

Measure \ Averaging	Arithmetic Mean
SHD	6.5
SAD	6.5
SSD	6.5
ZSAD	3.8
LSAD	4.7
ZSSD	4.7
LSSD	3.8
NCC	2.9

is the correlation measure that overcomes all the shortcomings of the others. Thus, as expected, the lowest EER is obtained through applying NCC. The fingerprints are converted to binary images after enhancement. Hence, there is no difference in computing the similarity score using SAD and SSD and SHD.

2.7.4.2 Properties of correlation-based techniques

To discuss the properties of the correlation-based fingerprint approaches the following points need to be considered: Correlation-based methods directly use the grey-level information from the fingerprint image. These methods take into account all dimensional attributes of a fingerprint which include micro characteristics such as minutiae, macro characteristics such as reference points, and also ridge shape, ridge thickness, etc [31, 32, 112, 102]. In other words, a fingerprint consists of ridges and valleys, so if a method works directly on all the available information from these two features, it has the potential of extracting all the discriminative information from a fingerprint. A grey-level fingerprint image contains richer, more discriminatory information than only the minutiae locations. Furthermore, in correlation-based methods false/missed minutiae do not decrease the matching performance and no hard decision needs to be made based on searching for minutiae pairs. Correlation-based methods are also capable of dealing with low quality

images. In terms of computational cost, correlation-based methods are expensive. However, there are different strategies to lower the computational effort:

- Reducing the search space for computing the correlation of two corresponding images by detecting the corresponding/common regions.
- Computing the correlation of the blocks of the images can be performed in parallel.
- The computation required to compute cross-correlation can also be achieved in Fourier domain (as described in [113]). The results of computation in both spatial and Fourier domains are equivalent but computation in Fourier domain is faster since translations are included in computation [102].

It should be mentioned that like many other problems in computer science, there is always a trade-off between accuracy and speed. Thus, although correlation-based techniques are more computationally expensive, they are more promising in improving the matching accuracy than minutiae-based methods in general, according to the above discussion.

2.7.5 Hybrid techniques

An example of the hybrid methods in this category is proposed by Nandakumar and Jain [31]. Their method is a hybrid of minutiae and correlation approaches. It is based on computing the correlation of small regions around minutiae. Their algorithm is shown in Figure 2.22. The first step in their method is to extract the minutiae from both template and query fingerprints. Then, a small window with the size of 42×42 pixels around the minutiae location in template fingerprints and with the size of 32×32 around the minutiae location in the query fingerprint is selected. The size of the windows in the template fingerprint is slightly greater

than the query fingerprint because of small errors in computing the minutiae location. For matching two fingerprints, the peak value of the correlation between the query and template windows is considered as the correlation between the two regions. The mean of the correlation value for all possible corresponding regions in the template and query is computed. All possible regions after the alignment stage are tested and the maximum correlation value is taken as the matching score between the template and query fingerprints. With regards to performance evaluation of this method, they compared their result with the minutiae-based method proposed by Jain et al. [114]. The EER was improved from *5.6%* to *5.1%*. Although their approach can sufficiently deal with non-linear distortion, it suffers from being dependent on the extracted minutiae. The two main problems of minutiae-based methods (working on limited information and detecting spurious and false minutiae) are also preventing this approach from providing a better result. As Nandakumar and Jain stated [31]: *"The local correlation-based matcher is not robust with respect to image quality and hence more work needs to be done to enable it to handle poor quality images."*

Another example of a hybrid method is that proposed by Abraham et al. [115] based on using shape and orientation descriptor. They stated that avoiding spurious/false minutiae and using landmarks (core and delta reference points) in addition to using ridge orientation cues can significantly improve the matching accuracy. Using shape Context descriptors in fingerprint matching was proposed by Kwan et al. [116] whilst Abraham et al. used a hybrid of shape and orientation descriptors for matching and filtering out the spurious/false minutiae and compensating for lack of landmarks in fingerprints.

The shape context is introduced by Belongie et al. [117] which is used as a feature descriptor in object recognition. The idea of shape context is that an object can be represented by a discrete set of points sampled from the object.

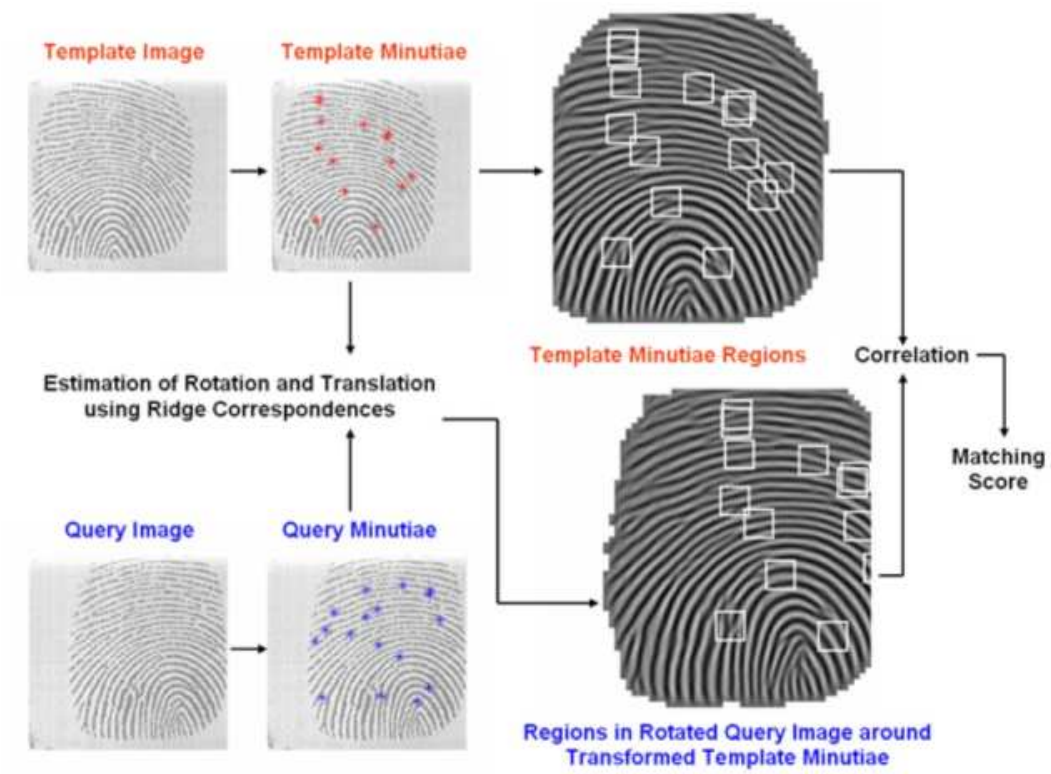


Figure 2.22: The proposed algorithm by Nandakumar and Jain [31] for local correlation-based fingerprint matching.

In the case of fingerprints, minutiae points are used. Assume that P and Q are the minutiae set extracted from query and registered fingerprint respectively, and there are n minutiae points in set P and m minutiae points in set Q. For every $p_i \in P$ the aim is to find the best matching minutiae $q_i \in Q$. As a result, for every minutia p_i, a coarse histogram h_i of the relative coordinates of the remaining $n-1$ minutiae is computed [116]:

$$h_{p_i}(k) = \sharp\{p_j \neq p_i \quad : \quad (p_j - p_i) \in bin(k)\} \tag{2.16}$$

The bins are uniform in the log-polar space (Figure 2.23). The cost of matching two minutiae points (one from each fingerprint) is calculated according to the following formula based on χ^2 test statistic [115]:

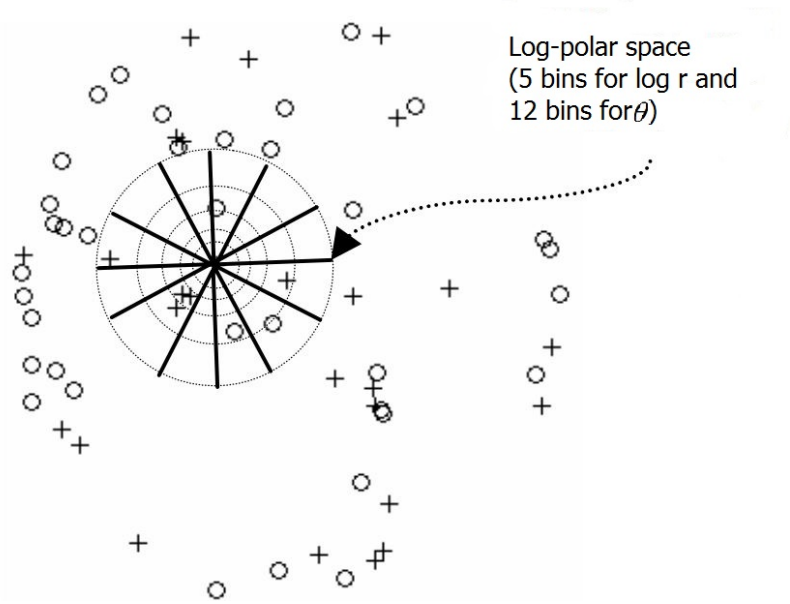


Figure 2.23: Log-polar histogram bins used to create shape context histogram of a fingerprint's minutiae. Bifurcation and ridge endings are denoted by '+' and 'o' respectively [116].

$$C_{ij} \equiv C(p_i, q_j) = \frac{1}{2} \sum_{k-1}^{k} \frac{[h_{p_i}(k) - h_{q_j}(k)]^2}{h_{p_i}(k) + h_{q_j}(k)} \tag{2.17}$$

The set of all costs C_{ij} for all pairs of minutiae p_i on the first and q_j on the second fingerprint are similarly computed with the aim of minimizing the matching cost.

2.7.6 Computing similarity/matching score

Matching/Similarity score is the value computed in a matching method to indicate how similar/dissimilar the two fingerprints are which enables the system to recognise the fingerprints as a match or non-match. The matching score could be computed differently depending on the features that a method is extracting and utilising to indicate the characteristics/properties of a fingerprint. Also, two different matching scores can be computed even if the same features are extracted. For instance, generally the matching score in minutiae based methods is computed

based on the number of matched minutiae points out of the total number of minutiae points extracted from query and registered fingerprints (i.e. Equation 2.10). However, if the quality of the region that each matched minutiae is extracted from is used as a factor to weight the matched minutiae (Equation 2.18) the matching score will be different.

$$MatchingScore = \frac{\sum_{i=1}^{k} w_i}{\frac{n+m}{2}} \tag{2.18}$$

where k is the number of matched minutiae between registered and query fingerprints. m and n are the number of minutiae points in registered and query fingerprints respectively. w_i is the normalized value of the region quality that minutiae i is extracted from.

In addition, the matching score can be computed globally and locally. A globally computed matching score refers to treating the fingerprints as one large single region whilst local matching refers to treating the fingerprints as multiple sub-regions which has been introduced in the last few decades [79]. Computing the matching score locally has the advantage of considering each sub-region separately and if a region is not able to provide accurate/desirable information (due to the low quality of sub-region) it will not affect other regions (Section 4.2). Also computing the matching score locally provide the option to further process the local matching scores through global score consolidation techniques (Section 4.3). Four global consolidation techniques were introduced by [79] which are discussed in Chapter 4.

To sum up, how the similarity/matching score of two fingerprints is computed is very important and can change the final match/non-match decision of the system (regardless of what feature is used). Chapter 4 presents a new algorithm to compute the matching/similarity score of fingerprints as one of the objectives of this research.

2.8 Performance Metrics

In a fingerprint recognition system, some physical characteristic of the fingerprint is mapped into a digital representation. For each individual, one of the representations is stored in the computer as the template. When the user is to be recognised, the system compares the stored template fingerprint to the presented fingerprint (query vs. template fingerprint). Given the complexities of physical characteristics, it is not expected that there will be an exact match between the two fingerprint images (Section 1.2). Rather, the system uses an algorithm to generate a matching score *"s"* that quantifies the similarity between the input and the stored template [100].

Figure 2.24 shows the dilemma posed to the system. If an individual is tested by the system several times, the matching score *"s"* will vary, with a probability density function typically forming a bell curve. In fingerprinting, the matching score may vary due to sensor noise, changes in the print due to swelling, dryness, finger placement, and so on (intra-class variation, refer to Section 1.2 for more details). On average, any other individual should have a much lower matching score but again will exhibit a bell-shaped probability density function. The difficulty is that the range of matching scores produced by two individuals, one genuine and one an imposter, compared to a given reference template, are likely to overlap. In Figure 2.24 a threshold value is selected thus that if the matching score $s \geq t$, a match is assumed, and for $s \leq t$, a non-match is assumed. The shaded part to the right of the threshold (*"t"*) indicates a range of values for which a False Accept (FA) or False Match is possible, and the shaded part to the left indicates a range of values for which a False Reject (FR) or False Non-match is possible. By moving the threshold, to the left or right, the probabilities can be altered, but note that a decrease in false match rate necessarily results in an increase in false non-match

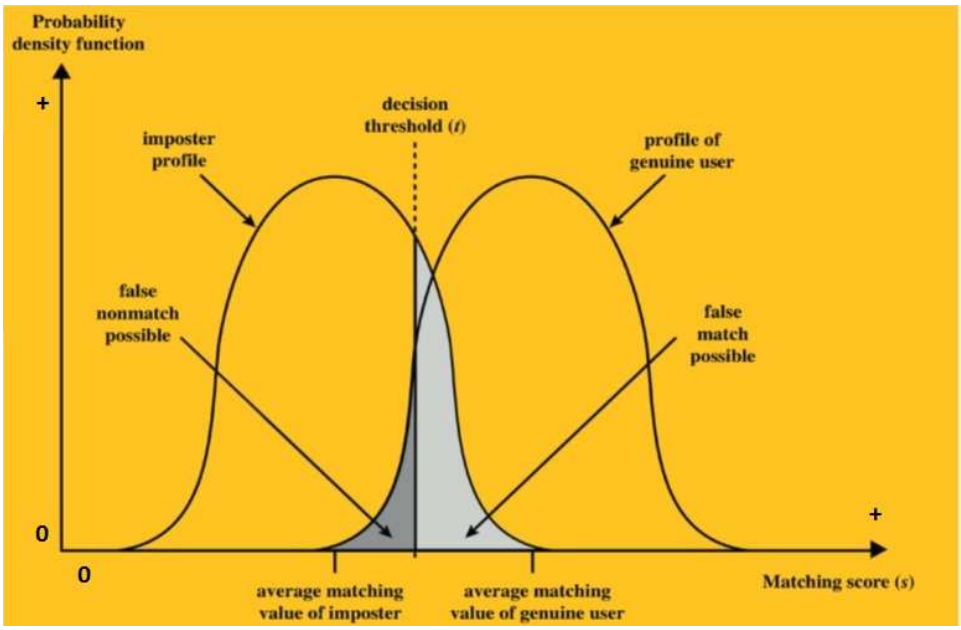


Figure 2.24: Profiles of a fingerprint characteristic of an imposter and a genuine user. If the matching score of two fingerprints is higher than a pre-defined threshold, it is considered a match [100].

rate, and vice versa [100].

False Acceptance Rate (FAR) is the ratio of FA to the total number of imposter matches (TI) expressed as a percentage, while False Reject Rate (FRR) is the ratio of FR to the total number of genuine matches (TG) expressed as a percentage.

$$FRR = \frac{FR}{TG} \times 100 \tag{2.19}$$

$$FAR = \frac{FA}{TI} \times 100 \tag{2.20}$$

There is always a trade-off between FAR and FRR. As a matter of fact, both of them are functions of the similarity threshold. An example of how FAR and FRR vary with the threshold is shown in Figure 2.25a. Assume that in an authentication system (FAR must be very low), FAR is 1%. This means that in every hundred attempts by imposters to access the system, one of them will be successful. Depending on application, this error rate may not be acceptable. Thus,

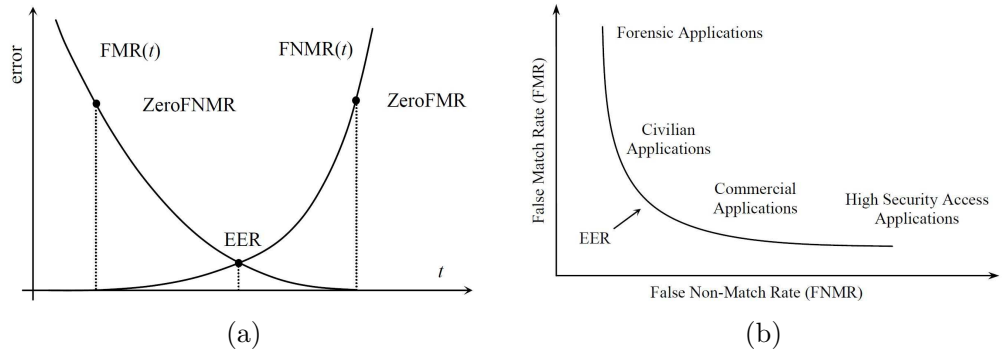


Figure 2.25: a) False Match Rate versus False Non-Match Rate, b) Operating points of different application on Receiver Operating Characteristic (ROC) curve

a metric called ZeroFAR was introduced [118, 119]. ZeroFAR is the FRR when FAR is set to zero. This metric is very useful to compare authentication systems. In authentication systems it is important to not accept anyone falsely (i.e. bank account access, ultra secret location access). For instance, only recognised people must have access to the bank vault. So the authentication methods try to reduce the FRR while the FAR is still zero or very close to zero (depending on the application). On the other hand, because of the trade-off between FAR and FRR, when the FAR is set to zero, the value of FRR will be high. This means that the system will reject the authorised person so he/she has to try again to get the system approval [120].

On the other hand, while not rejecting an authorised person is important, another metric called ZeroFRR [118, 119] is used. ZeroFRR denotes the FAR when FRR is set to zero. This is a good metric to compare biometric systems their goal is to never reject an authorised person. In this case granting access to an authorised person is more important than accepting an unauthorised one. An example of applications where this metric is useful in forensic application. In latent fingerprint recognition, the system should not reject the person to whom the latent fingerprint belongs. In this case, the system may falsely accept other people as a match for the latent fingerprint but the true match should not be missed.

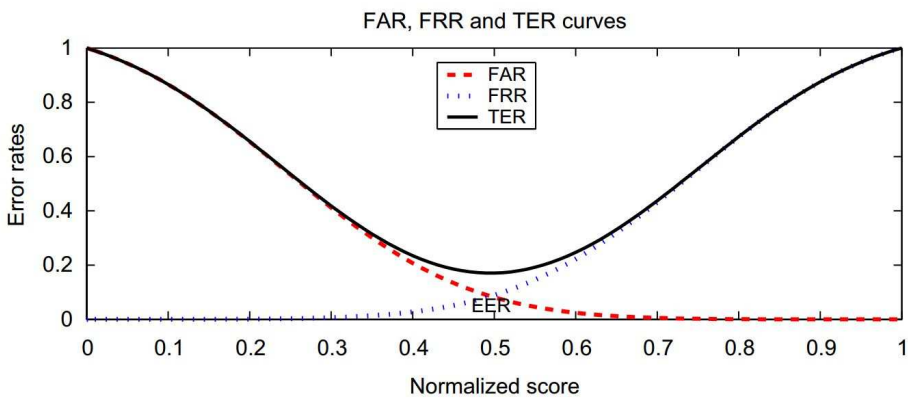


Figure 2.26: Relations among FAR, FRR, TER, and EER [123].

Another metric is Equal Error Rate (EER) [118, 119]. EER is as a good indicator of system performance which denotes the error rate when both FAR and FRR are identical. EER is a popular metric because in some applications, not giving access to an unauthorised person (low FAR) is as important as giving access to an authorised person (low FRR). As Figure 2.25b depicts, EER is a useful metric in civilian and commercial applications. The lower EER means better system performance since the lower EER means lower FAR and FRR at the same time in the system. Another metric, similar to EER is Total Error Rate (TER) which is the sum of the FAR and FRR. As stated in [121], EER, TER, FAR and FRR are most commonly used and generally applicable metrics in testing biometrics system performance. Figure 2.26 shows the relationship among these metrics. As shown, in a normal distribution of genuine and imposter users, TER is always greater than EER as it sums the FAR and FRR. Since it also makes sense to have a measure that is of the same order as FAR and FRR, sometimes TER is modified to Half Total Error Rate (HTER) which is calculated as $HTER = \frac{FAR+FRR}{2}$ [122].

2.9 Conclusion

In this Chapter the literature on fingerprint matching techniques was reviewed. As part of the matching algorithms, fingerprint images are enhanced first (in terms of quality) to increase the clarity of ridges and valleys. Enhancement leads to the extraction of more reliable features from fingerprints and subsequently an improvement in the matching decision. The three level of features discussed and showed that methods that are using more detailed features could improve the matching accuracy. Also the reliability of the extracted features as well as their discriminative capability using features other than (or in addition to) minutiae-points, can improve the system error rate. One of the most promising approaches in order to extract all the available information in a fingerprint is a region-based approach. Region-based approaches work on every pixel of the images and utilise all the available features in fingerprint.

Typically, there are different steps in fingerprint matching methods, consisting of feature selection and extraction, fingerprint alignment, computing similarity score and etc. In some cases, in order to evaluate the improvement achieved through different steps, all the other steps need to be performed as well. Figure 2.27 shows the high level block diagram of the fingerprint matching method. When a query fingerprint is presented to the system, it is compared with the registered fingerprint. Fingerprint enhancement (Section 2.4.1) is one of the preliminary steps in most of the fingerprint matching methods as the quality of fingerprints may be low and with an enhancement method, their quality can be improved. Segmentation refers to separating the image background from the fingerprint area. Segmentation can be performed by applying a mask technique (e.g. a region of size 20×20 pixels where all the pixel values are identical). If all the or majority of the pixel values are identical in a 20×20 region, it is either a highly distorted

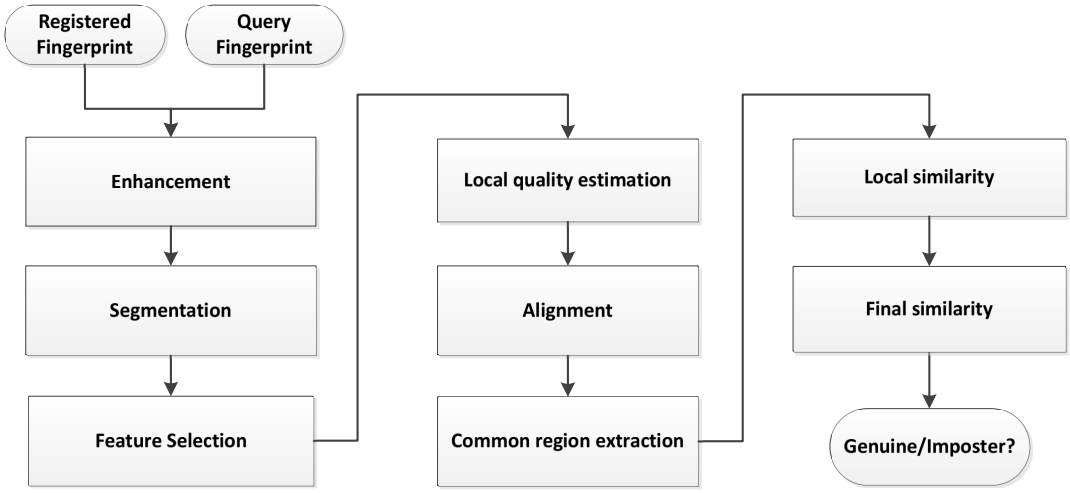


Figure 2.27: High level block diagram of the proposed fingerprint matching method.

region or fingerprint background area.

Feature selection is one of the most important parts of a fingerprint matching method. There are many different features to extract from a fingerprint (Section 2.6) and depending on the extracted features, the system performance could be significantly affected due to the reliability and distinguishing characteristics of the feature(s). The registered and query fingerprints need to be aligned as their corresponding regions are going to be compared. Fingerprint alignment refers to making the two query and registered fingerprint rotationally identical. After alignment, the common regions between the two fingerprints can be detected. Identifying the common regions will improve the accuracy of local similarities and also efficiency of the recognition process as only a one to one comparison of sub-regions is performed to compute the local similarities (not one sub-region versus the whole other fingerprint). A set of values, known as local similarities, are consolidated to represent a single value of final similarity between the two fingerprints. The final decision of whether the query and registered fingerprints are from the same finger is made upon the final similarity value.

With regards to addressing the issues in partial fingerprint matching, as dis-

cussed, the issues in partial fingerprint matching are almost the same as full fingerprint matching, except that the amount of available information in a partial fingerprint is less. Thus, in order to increase the accuracy, specially in partial fingerprint matching, the information limitation needs to be considered. Therefore, the proposed alignment method considers this limitation and is based on the fingerprint ridge structure only which is available in a partial fingerprint.

Alignment is an important step in fingerprint matching and the more accurate fingerprints are aligned, the higher the degree of confidence is in matching. That is mainly due to the more accurate common region extraction as part of the matching procedure and subsequently more reliable local similarities that are computed for common regions between the two fingerprints. Chapter 3 discusses the proposed alignment and common region extraction methods.

In addition, since the quality of partial fingerprints might be poor, the metric used to compute the similarity score should not be sensitive to the image quality as well as being able to reflect the characteristics of the fingerprint based on the available information. Also, when combining the local similarities into a final value, the final similarity score of the partial fingerprints should compensate for the skew in local similarities as the quality of the partial fingerprints might vary in different regions. Computing the local and final similarity score of fingerprints is discussed in Chapter 4.

Chapter 3

Fingerprint Alignment

3.1 Preamble

In the previous chapter, the techniques used for full and partial fingerprint recognition were reviewed and two major research challenges that need to be addressed in this work were identified. These two challenges are *(i)*, how to align the full and partial fingerprint to simplify the matching process and overcome the rotational difference between the two fingerprints and *(ii)*, how to assign the matching/similarity score to a pair of fingerprints to compensate for high intra-class variation and inter-class similarity. This chapter addresses the first objective of this research by proposing a partial fingerprint alignment method to rotationally align a pair of fingerprints and locate their corresponding regions. The next Chapter addresses the second objective of the research on measuring the similarity score of the fingerprints in a region-based manner after the fingerprints are rotationally aligned and their common regions are located. The result achieved through these two chapters are compared with other works in Chapter 5.

One of the intra-class variations is the rotation and/or translation difference between two fingerprints. In a pixel to pixel comparison of two images, even a slight rotation difference between the two images, could result in a wrong matching

decision. In other words, an accurate alignment will result in minimizing false decisions in the system. This chapter discusses the fingerprint alignment as one of the objectives of this thesis to address the difficulties of partial fingerprint alignment and propose an alignment method that is able to rotationally align the fingerprints by considering the difficulties of partial fingerprint alignment such as availability of limited information. The previously developed fingerprint alignment methods, including minutia-based and non-minutia feature based ones, may not be suitable for partial fingerprints [72]. One issue of applying these methods to partial fingerprints is that there may be few required features on fingerprint fragments. Accordingly, they will either lead to incorrect alignment or not be applicable [72]. For instance, Khalili et al. have investigated on using fingerprint reference points to rotationally align the fingerprints [73]. However, it is likely that reference points are not available in partial fingerprints. Therefore, it is critical to align the partial fingerprints only based on the available features [21].

In addition, since the shape and size of the partial fingerprint is not fixed, the fingerprints must be aligned adaptively to the partial fingerprint shape and size. In order to align the fingerprint (full and partial), two alignment methods are proposed. The first method is based on the correlation of fingerprints sub-regions (Section 3.2.1) and fingerprint singular points (Section 3.2.2). The second method focuses on fingerprint alignment based on the correlation of fingerprints sub-regions (Section 3.3). By considering the surrounding regions in region-based matching, the rotation difference of the two fingerprints can be obtained even more accurately. As the performance evaluation of these two methods shows (Section 3.3.4) alignment by only using the fingerprint ridge performs slightly better compared to using singular points for coarse alignment. However, when accuracy is not the main focus of the system, using the singular points (if available) is reasonable due to the faster process of aligning the fingerprints.

Aligning the two fingerprints provides information that can be used to recognize some fingerprints with a high degree of confidence and without any further process. If the two fingerprints that are compared do not present high intra-class variation or high inter-class similarity, the match-non-match decision can be made at this stage which increases the matching time efficiency (Section 3.4). The experimental result of using this information for recognition is reported in Section 3.5. In other cases, the two fingerprints need to go through the next matching step which are common region extraction and local and global similarity computation.

When the fingerprints are aligned, in order to compute the similarity of fingerprints locally (Chapter 4), the common regions between the fingerprints need to be identified. As the fingerprints are usually two dimensional images, locating a common offset point in both images can be used to identify the corresponding regions. The offset point is obtained through the alignment process. Detecting the common/corresponding regions between the two registered and query fingerprints is discussed in Section 3.6.

3.2 Alignment Based on Fingerprint Ridge and Singular Points

Using fingerprint ridge structure (Section 3.2.1) is suitable for partial fingerprint alignment since it is not dependent on any particular feature (such as singular points) that may not be available in a partial fingerprint. Also, as discussed in Chapter 2, fingerprint ridge structure provides richer information compared to the level 2 features (Section 2.6.2). In addition, aligning the fingerprint based on the fingerprint ridge structure is not dependent on the shape and size of the partial fingerprint since as long as a partial fingerprint is provided, it contains the fingerprint ridge (even if it is a small area). However, if the singular points

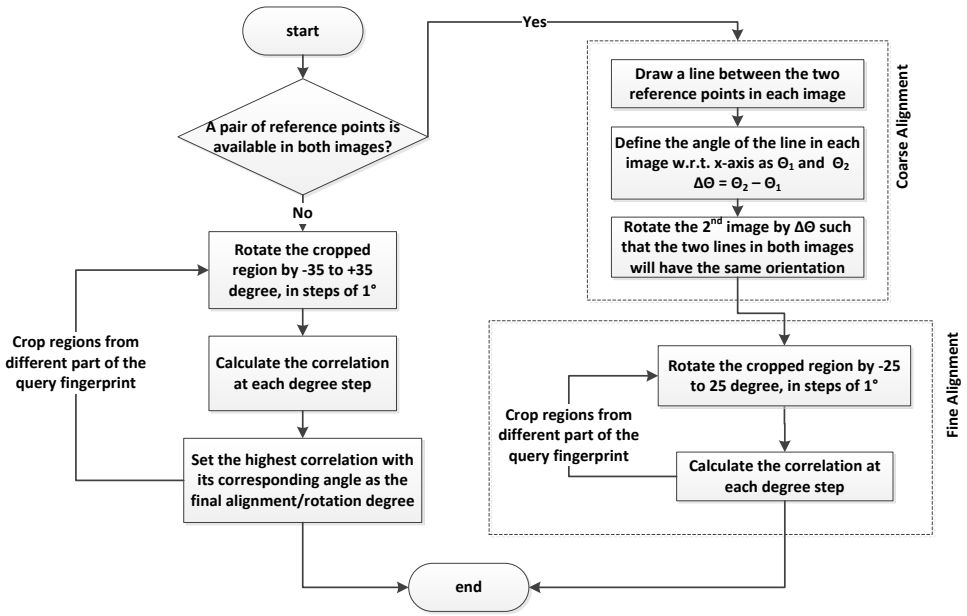


Figure 3.1: Block diagram of the proposed alignment method based on fingerprint ridge and singular points.

are available, they could be used for a coarse and fast alignment as described in Section 3.2.2. In this section, alignment of fingerprints based on the fingerprint ridge structure and singular point features is discussed. The advantages of this method in terms of accuracy and time efficiency along with the experimental results is reported. The block diagram of the proposed method for alignment is presented in Figure 3.1.

3.2.1 Alignment based on fingerprint ridge structure

As discussed in Section 2.7.4, the region-based comparison include more discriminative information than minutiae-features for matching while being more reliable with respect to the image quality. The same discussion is applicable for the features to use to align the fingerprints.

The alignment process starts with cropping a region from the query fingerprint.

The size of the cropped region can vary depending on the size of the valid fingerprint regions. For each of the cropped regions, the correlation of the cropped region and the registered fingerprint is computed for different rotation angles. The rotation angle which gives the highest correlation value, is used to rotationally align the two fingerprints. In addition, the region can be cropped from different parts of the query fingerprint. In order to crop different regions with different sizes from query fingerprints, the query fingerprint is divided into sub-regions. The sub-regions that are fully occupied with fingerprint information (not part of the background) can be selected. These two properties make this strategy suitable for partial fingerprints alignment since it is independent from the fingerprint shape and size and uses the rich ridge structure information that is available in a partial fingerprint.

By aligning the fingerprints in this way, partial fingerprints can be aligned even though there is no singular point available. In addition, the fingerprints are aligned since the finger skin elasticity is handled and the effect of distorted regions on the fingerprint is ignored, as different regions (with different sizes) can be cropped from the query fingerprint. The result of aligning by this strategy is shown in Figure 3.2. Although this strategy is accurate, it is not efficient in terms of computational cost. Each cropped region is rotated by -35 to $+35$ degree till the rotation difference is found. In order to increase the efficiency, the singular points position (if available) on the fingerprint is used as the second strategy.

3.2.2 Alignment based on singular points

The fingerprints are generally 2-dimensional images which can be rotationally aligned if two identical points can be located in both images. Singular points (if available) could be used to align the fingerprints *efficiently* based on this theory. Singular points are part of the level-1 features (macro features); explained

(a) (b) (c)

Figure 3.2: Impressions of the same finger being aligned based on computing the correlation of their ridge structure. a) registered fingerprint b) query fingerprint c) aligned query fingerprint

in Section 2.6. However, there are two problems which make using the singular points not a perfect plan for alignment. First is due to the intra-class variation that makes the location of the singular points vary from one fingerprint to another (in intra-class) which may result in inaccurate alignment. Second is the mislocation of these singular points. This strategy relies on identifying the location of the singular points and depends on the method applied to identify the singular point location. The singular points locations are detected based on the method proposed by Wang et al. [124]. To investigate the effect of the intra-class variation as well as singular points mislocated by the method, the following experiment was conducted:

The ideal situation in intra-class cases is that the location of any singular point in one image be identical to the location of the corresponding singular point in the other image. For instance, the difference in the Euclidean distance between core and delta points in two intra-class fingerprints "R", and "Q", should be very small. If so, the idea of using the singular point location for alignment is promising. Considering the four types of singular points in a fingerprint (upside core, downside core, right delta, and left delta), there are six pair of singular points (*(upside core, downside core), (upside core, right delta), (upside core, left delta), (downside core, right delta), (downside core, left delta) , (right delta, left delta)*).

Figure 3.3 shows the plot of subtracting the Euclidean distance between singular points of intra-class and inter-class fingerprints which is computed as follows:

Assume that two pairs of the same reference points exist in both fingerprints. If $C_R(x_1, y_1)$ and $D_R(x_2, y_2)$ are core and delta points respectively in the registered fingerprint, likewise $C_Q(x'_1, y'_1)$ and $D_Q(x'_2, y'_2)$ are core and delta points respectively in the query fingerprint, subtracting the Euclidean distance between core and delta points of the two fingerprints is:

$$\begin{aligned} EuclideanDistance(C_R, D_R) - EuclideanDistance(C_Q, D_Q) = \\ \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} - \sqrt{(x'_1 - x'_2)^2 + (y'_1 - y'_2)^2} \end{aligned} \tag{3.1}$$

If the value of Equation 3.1 is very low, it means the two singular points in each fingerprint are at the same distance from each other. In other words, if value of Equation 3.1 is very low, it shows the fingerprints are (significantly) affected by distortion.

The experiment is conducted on the public data set FVC2002_DB1. As shown, in many cases the subtraction between the Euclidean distance of the two pairs of singular points locations in intra cases is lower than those in inter-cases (desired; *as it indicates lower intra-class variation*). This reveals the potential of using the singular points location for alignment. In such cases alignment based on the position of singular/reference points will be accurate. On the other hand, in some intra-cases, this value is more than the ones in inter-cases due to the intra-class variation (undesired). In this case, aligning the fingerprints based on the position of reference points will not be accurate, but it still could be used for a *coarse alignment* (to take advantage of the efficiency of this strategy). This could occur due to two reasons. First, the intra-class variation makes the singular points far from each other. Second, the algorithm to detect the singular points is not

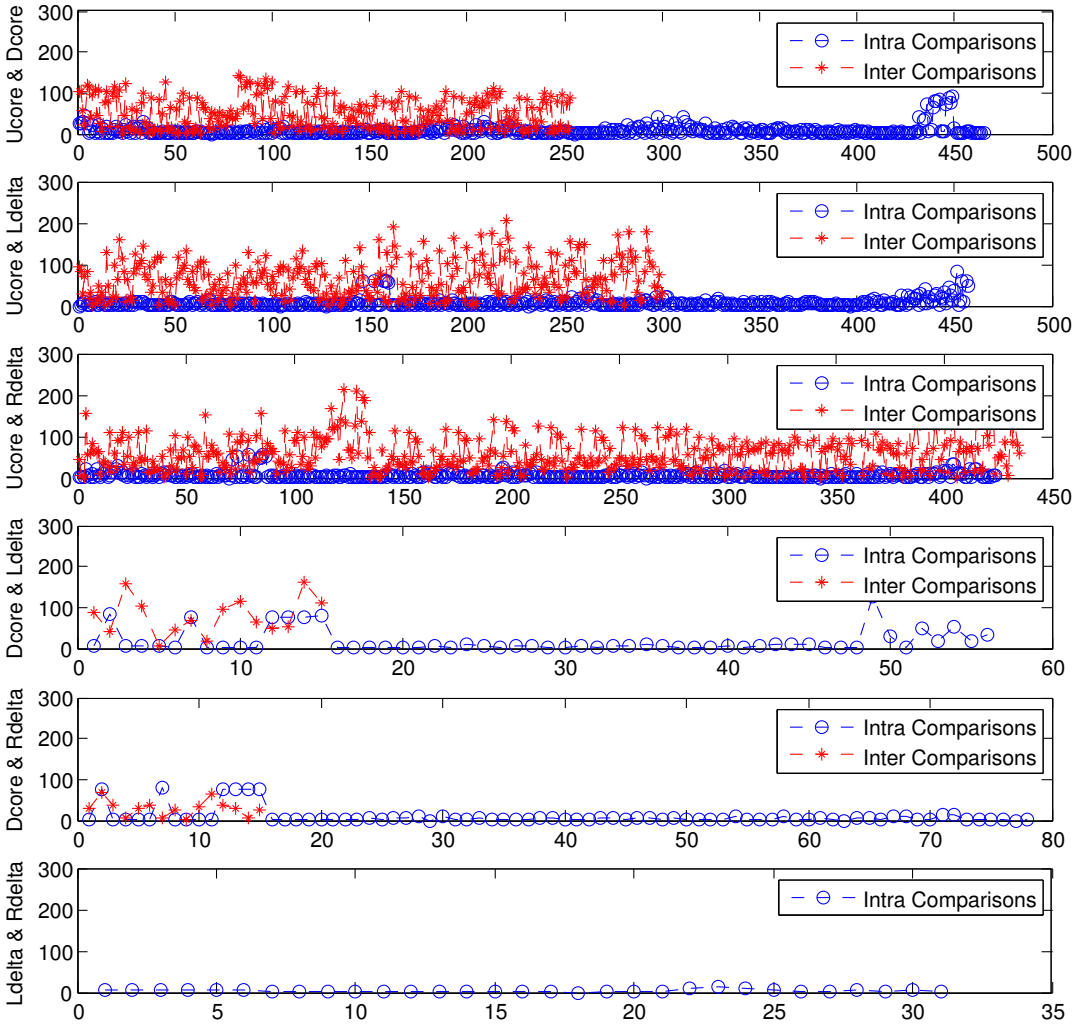


Figure 3.3: y-axis indicates the difference between the Euclidean distance between each pair of singular points in intra and inter class fingerprints (in pixels), x-axis indicates a comparison in inter/intra. Ucore = upside core, Dcore = downside core, Ldelta = left delta, and Rdelta = right delta.

perfectly accurate and in some cases the singular points are mis-located. Therefore, a coarse alignment could be achieved by using the signular points location which is useful when the speed of the method is more important than the highest possible accuracy.

Assume two pairs of the same reference points exist in both fingerprints. To align them based on their position and angle with respect to x-axis, the query image is rotated till the gradient of the line between the two common reference

points are identical and therefore the two fingerprints will be rotationally aligned. If $C_R(x_1, y_1)$ and $D_R(x_2, y_2)$ are core and delta points respectively in the registered fingerprint, likewise $C_Q(x'_1, y'_1)$ and $D_Q(x'_2, y'_2)$ are core and delta points respectively in the query fingerprint, the angle between (C_R, D_R), and (C_Q, D_Q), (θ_1 and θ_2 respectively) is computed as follows:

$$\theta_1 = tan^{-1}(\frac{y_2 - y_1}{x_2 - x_1}), \qquad \theta_2 = tan^{-1}(\frac{y'_2 - y'_1}{x'_2 - x'_1}) \tag{3.2}$$

$$angle = \theta_2 - \theta_1 \tag{3.3}$$

Equation 3.3 indicates the angle that query fingerprint must be rotated in order to be aligned with the registered fingerprint.

Figure 3.4 illustrates an example of aligning the fingerprints based on the above process. Figures 3.4a and 3.4b show the registered and query fingerprints respectively, which are different impressions of the same finger. To align the query fingerprint with the registered one, the query fingerprint should be rotated clockwise. The red and green circles depict the location of up-core and delta respectively on both of the fingerprints. According to the position of the core and delta points on the registered image and by using Equation 3.2, $\theta_1 = +111°$ and likewise $\theta_2 = +116°$. Then the angle (Equation 3.3) is $-5°$ which means the query image should be rotated by 5° (clockwise) to be aligned with the registered image (Figure 3.4c). In this case, the singular point detection method correctly identified the position of the singularity, but due to the intra-class variation, core and delta points changed their position in two different impressions. In these cases using the position of the singular points will not result in an accurate alignment. However, the fingerprints were coarsely aligned which improves the alignment efficiency in total.

In order to overcome the mentioned limitations, combining the two strategies

(a) (b)

$\theta_1 = +111, \theta_2 = +116, angle = \theta_1 - \theta_2 = -5$

(c) (d)

Figure 3.4: Aligning the query fingerprint (b) with respect to registered fingerprint (a), in (c) only macro features used to align the fingerprints, in (d) alignment is done by using both macro and micro features.

(Alignment based on micro and macro features) is promising.

3.2.3 Alignment by hybrid of fingerprint ridge and singular points

Considering these two strategies, combing the above two alignment strategies results in taking advantage of efficient alignment by using singular points (coarse alignment) and fine alignment by using the fingerprint ridge. So the result will be an improvement to the efficiency of alignment by the fingerprint ridge structure

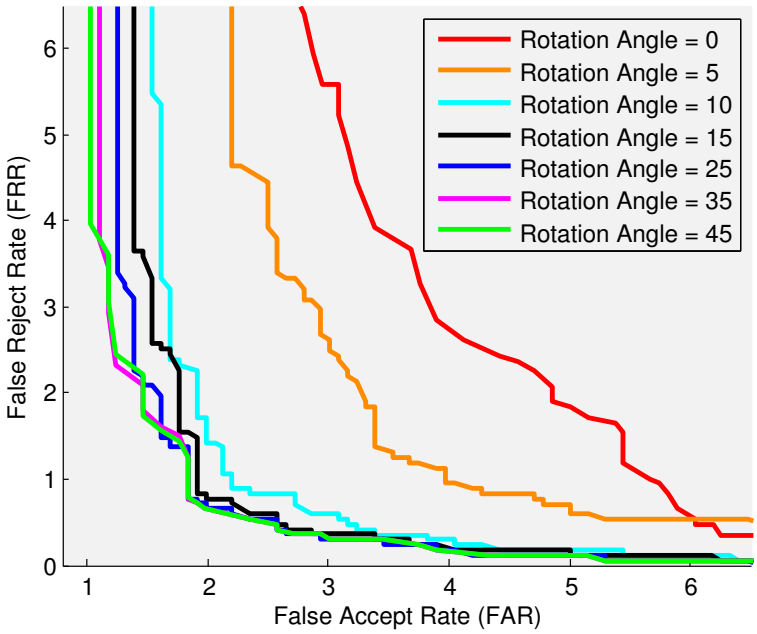


Figure 3.5: ROC of the proposed method by using different rotation angles in second alignment strategy.

which is suitable for partial fingerprints. Figure 3.5 shows the ROC plot of the discussed alignment method. Each curve shows the False Reject Rate (FRR) versus False Accept Rate (FAR) (refer to [119] for FAR and FRR explanation) for different degree of rotation used in Section 3.2.1. This experiment is conducted only on the fingerprints in FVC2002 DB1 dataset that one pair of singular points were available in both registered and query fingerprints. The red curve shows the system performance when rotation angle is set to zero which is equivalent to only applying the alignment strategy in Section 3.2.2 (coarse alignment). As depicted, by increasing the rotation angle (in first strategy), the Equal Error Rate, EER (where FAR = FRR, [119]) decreases. This is due to the robust (but more time consuming compared to first strategy) alignment by rotating the query image with respect to the registered image. This technique overcomes the problems experienced when the alignment method depends on the use of singular points.

3.2.4 Summary of the alignment by using fingerprint ridge and singular points

In this section the first method to rotationally align the fingerprints is discussed. The two kind of fingerprint features utilized in this study are introduced and the advantage of combining them together in order to improve the efficiency without loosing accuracy is explained. Singular points are used to coarsely align the fingerprints (Section 3.2.2) and fingerprint ridge structure is used for fine alignment (Section 3.2.1) regardless of the singular points existence. However, the fine alignment is based on the highest similarity achieved by overlapping the cropped region from query fingerprint on registered fingerprint and offering the highest similarity obtained through overlapping (sliding) the two regions. The issue is that the highest similarity value achieved (through overlapped regions) might not *always* be the correct value to select. The presence of more than one peak (highest similarity by overlapping two sub-regions) with approximately the same value shows the probability of choosing the wrong peak. Thus, in order to achieve further accuracy through the micro features, the next section discuses the alignment based on fingerprint ridge structure as well as considering the global structure of the fingerprint ridge.

3.3 Alignment Based on Fingerprint Ridges only

The correlation scores obtained from overlapping a region (cropped from query fingerprint) on a registered fingerprint may be plotted as illustrated in Figure 3.6. The correlation maximum score of comparing two regions might not always be the correct correlation or not correspond to the global structure of the fingerprint. It is probable that more than one peak (of approximately the same height) exists. That increases the probability of choosing the incorrect peak. Also a situation

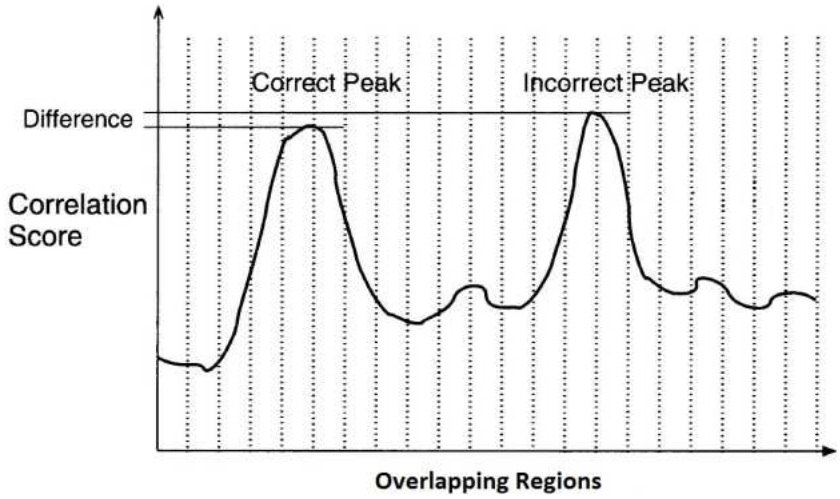


Figure 3.6: Correlation score of overlapping a region on another image [103].

may happen that the correct peak is slightly lower than the false peak [103].

Correct and incorrect peaks are defined according to the global structure of the fingerprint that is measured by considering the other available sub-regions in the query and registered fingerprint. In some cases the highest correlation might be achieved by overlapping two sub-regions of registered and query fingerprint, however if the second highest correlation value is considered by taking into account the surrounding regions, the result might be more accurate as it corresponds to the global structure of the fingerprint. Figure 3.7 illustrates the situation that the highest peak does not result in assigning highest possible similarity to the intra comparisons. Figure 3.7a shows the query fingerprint and Figure 3.7b shows the cropped region from the query fingerprint. The highest correlation value was achieved when overlapping Figure 3.7b on the region indicated in Figure 3.7c. The second highest value was achieved by overlapping it on the region shown in Figure 3.7f. The other sub-regions cropped from query fingerprint show higher consistency (in terms of the corresponding sub-regions between query and registered fingerprint) to the sub-region shown in Figure 3.7f (the second highest value). In this case, since the other regions show higher consistency to the cropped region

when the second highest value is selected, it indicates that choosing the second highest peak may corresponds more to the global structure of the fingerprint than the highest peak (this results in assigning higher similarity to an intra comparison). Table 3.1 shows the NCC value, (x, y) location of the cropped region from the query fingerprint and (x, y) location of the overlapped region on the registered fingerprint as well as the ranked value according to the number of region showing consistency to the cropped region from query fingerprint. According to the ranked value, the result of the overlapping cropped region on the region shown in Figure 3.7f is more reliable, though the NCC value of overlapping on region shown in Figure 3.7e is higher. The details of the ranking strategy is discussed in Section 3.3.3.

In order to assess the highest reliable sub-region to be used for alignment by considering the global structure of fingerprints, the second alignment method is presented which follows the block diagram shown in Figure 3.8. The next subsections explain the steps need to be taken in order to align the fingerprints as described in Figure 3.8. Since in this method, fingerprints are treated locally by dividing them into sub-regions, sub-section 3.3.1 discusses the image decomposition. After the query fingerprint is divided into sub-regions, each one of the sub-regions are overlapped with the registered fingerprint to obtain the initial value of rotation difference between the two fingerprints, (x, y) coordinates of where the sub-region overlaps on the registered fingerprint, and the correlation between the sub-region and registered fingerprint (Sub-section 3.3.2). Sub-section 3.3.3 defines how the sub-regions are ranked in order to identify the sub-region that shows the highest consistency with other available sub-regions. The sub-region that is assigned with the highest rank is used for: *(i)*, rotating the query fingerprint according to the angle that this sub-region was rotated by (to rotationally align the fingerprints); and *(ii)*, the coordinate that this sub-region was cropped from in the query finger-

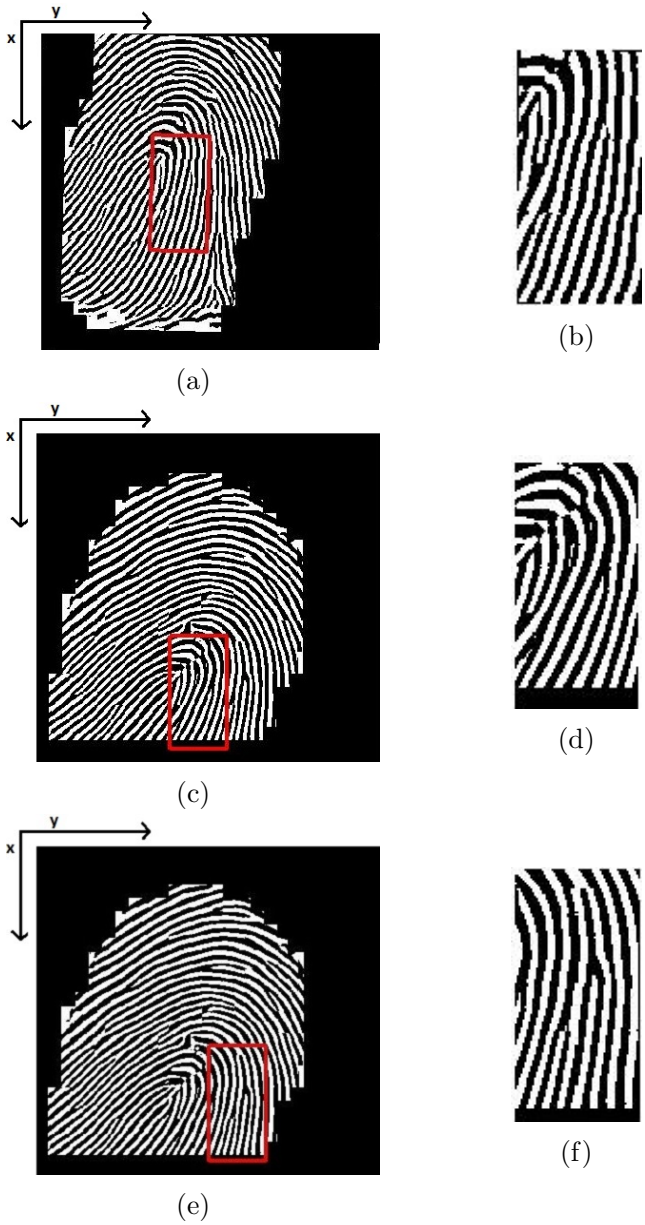


Figure 3.7: a) query fingerprint. b) cropped region from query fingerprint. c) and e) registered fingerprint. d) the region on registered fingerprint that gives the highest NCC value f) the region on registered fingerprint that gives the second highest NCC value.

print and the coordinate that it overlapped on the registered fingerprint is used as the off-set point to extract the common region between the two fingerprints is discussed in Section 3.6.2. It should be mentioned that in this case, the common regions between the two fingerprints are detected independent of any particular

Table 3.1: Result of overlapping cropped query fingerprint (Figure 3.7b) on region Figure 3.7d and Figure 3.7f from registered fingerprint.

overlapping Figure 3.7b on ...	Figure 3.7d	Figure 3.7f
correlation value	0.4784	0.4128
(x, y) of cropped region from query fingerprint	(356, 216)	(352, 259)
(x, y) of cropped region from registered fingerprint	(256, 192)	(256, 192)
Ranked value	0.4784	0.5367

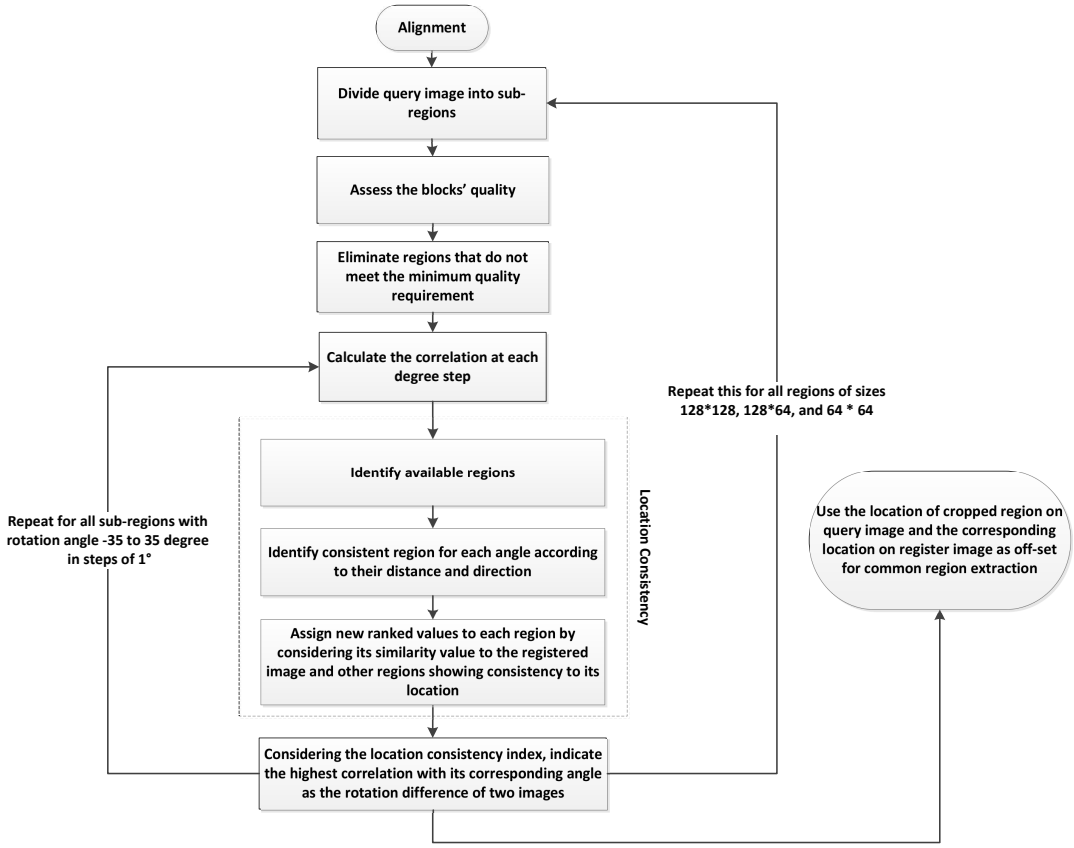


Figure 3.8: Block diagram of the improved alignment method (method 2).

feature such as singular points (suitable for partial fingerprints). Also, the information in this stage (ranked sub-regions) can be used to recognise the fingerprints without any further processing as described in Section 3.4.

3.3.1 Image decomposition

Considering the intra-class variation (Section 1.2) and different quality in different regions of the fingerprint (Section 2.4.1), the images are decomposed into sub-regions. In addition, at this stage, it is not clear that which regions in the query fingerprint are available in the registered fingerprint. It emphasizes the need to decompose fingerprint into sub-regions and treat each one of the sub-regions separately to find its match in the registered image. Where there is a highly distorted region in a query/registered fingerprint, that region does not provide accurate information to align the fingerprints based on the similarity of the sub-region and registered image. Instead they are aligned using a region-based metric and as the fingerprint quality mainly refers to the clarity of ridges and valleys, a poor quality region is less likely to find the corresponding regions in the registered fingerprint. In addition, the size of the sub-regions should not be too small or too big. If the size of the selected region is too small, it contains few fingerprint ridges which may not be enough information for an accurate alignment. Also regarding the size of the sub-regions, a too small region can be too sensitive to the distorted regions (and intra-class variation) of the fingerprints and is likely to be matched with an incorrect region of registered image (as it contains limited information). On the other hand, if the size of the selected region is too big, it may be less sensitive to the distorted parts (which is desirable), but it fails to overcome the non-linear distortion in the fingerprint. Also, a sufficiently large region may not be available in the partial fingerprint. Thus, the query fingerprint is decomposed into sub-regions with different sizes and the effect of the size is considered in its ranking (Section 3.3.3). It should be noted that the word "sub-regions", refers to the regions that are fully occupied by fingerprint information (not those containing the image background).

Considering the size of the fingerprints in the dataset, the size of the sub-regions

Figure 3.9: A query fingerprint decomposed into sub-regions. (x, y) is used as the sub-region index.

is set to 128×128, 128×64, and 64×64. Figure 3.9 shows the query fingerprint that is decomposed into sub-regions of the size 64×64 which provides simple extraction of the sub-region with bigger sizes (by concatenating the adjacent regions). In order to assure that sub-regions that could provide the most reliable information are selected, they need to pass the quality test as described in Section 2.5.

3.3.2 Matching the selected sub-regions with registered fingerprint

After the valid sub-regions are identified, they are matched (overlapped) rotationally and translation-ally with the registered image. This is done by rotating each sub-region with different angles and storing the set of three values achieved:

angle, the similarity value, and the location providing the highest overlap. The first parameter is the angle that the sub-region is rotated with. As indicated in Figure 3.8, each region is rotated from -35 to $+35$ degrees (it is the highest rotation difference as mentioned in the dataset description). This parameter is used to rotate the whole query fingerprint *if* this angle provides the highest similarity among all the other regions and angles. The second parameter is the highest similarity achieved by overlapping the sub-region on different possible locations on the registered fingerprint. This parameter is used to compare the highest similarity achieved through different sub-regions and angles (in order to find the best rotation difference of the two fingerprints). The third parameter shows the (x, y) location of the query fingerprint that the sub-region was cropped from and (x', y') location of the registered fingerprint that the sub-region was overlapped with (and produced the highest similarity). The location refers to the bottom right corner of the sub-region that is cropped from registered/query fingerprints (as shown in Figure 3.10). The third parameter is used to identify the corresponding regions as described in Section 3.6 as well as checking the consistency between the sub-regions as in Section 3.3.3.

3.3.3 Ranking strategy according to the other sub-regions

As mentioned in Section 3.2.4, the second method of alignment takes into account the information provided from all the regions in order to increase the reliability and accuracy of the alignment. As mentioned in the previous section, for each sub-region, three parameters are recorded. To make sure the correct angle (obtained from comparing two sub-regions) that shows the rotation difference between the two fingerprints is selected, the location and direction of the other sub-regions are taken into account. The following explains the procedure to do so.

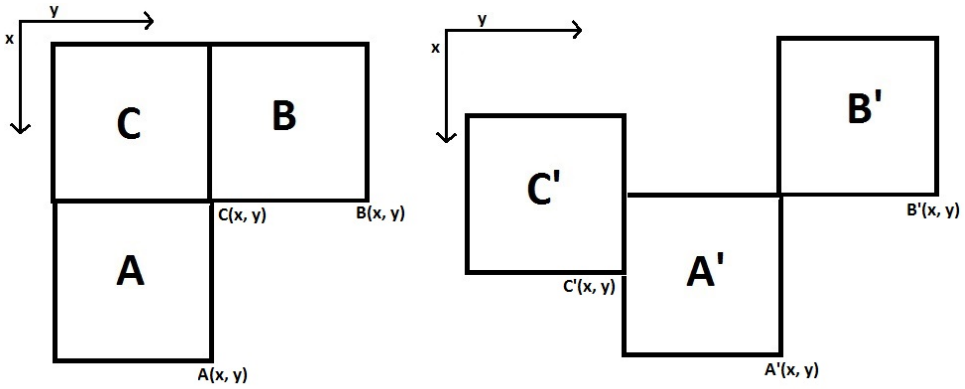
Table 3.2 shows the result of overlapping a cropped region from a query fin-

Table 3.2: Result of overlapping cropped region from query fingerprint on two regions from registered fingerprint.

	Region 1	Region 2
angle	-9	6
correlation value	0.4424	0.4128
Number of sub-regions showing consistency	0	4
Number of other sub-regions	3	6
(x, y) of cropped region from query fingerprint	(356, 216)	(352, 259)
(x, y) of cropped region from registered fingerprint	(256, 192)	(256, 192)
Ranked value	0.4424	0.5367

gerprint on two different regions of a registered fingerprint (intra-comparison). As indicated by the "number of other sub-regions" in the table, there are 3 and 6 other sub-regions that could be used to validate the reliability (assign ranking) to the information provided by overlapping the cropped query sub-region on Sub-Region 1 and Sub-Region 2 of registered fingerprint respectively. For each one of these 3 and 6 other sub-regions, the (x, y) location of where the highest similarity is achieved is recorded. According to this information provided by other sub-regions cropped from the query fingerprint, the reliability of the highest peak obtained from overlapping the cropped sub-region on the registered fingerprint (which resulted in highest similarity with the angle -9 and 6 in this example) can be assessed. According to the assessment, a ranked value is assigned to the cropped sub-region in order to compare it with others and align the query and registered fingerprints based on the most reliable (highest ranked) sub-region. The ranking is performed based on the location and angle of the highest peak value achieved by other sub-regions that have been cropped from the query fingerprint and overlapped on the registered image.

Figure 3.10 shows an example of the available cropped regions from a query fingerprint (indicated as A, B, C) and their corresponding regions on a registered fingerprint (A', B' and C' respectively). If "A" is the sub-region to be ranked, the angle and distance differences of A and B versus A' and B', A and C versus A'



(a) (b)

Figure 3.10: An example of a) three sub-regions cropped from query fingerprint and b) their corresponding regions on registered fingerprint.

and C' is computed. For instance, the angle and distance differences of A and B versus A' and B' is computed as:

$$EuclideanDistance_{(A,B)} = \sqrt{(A_x - B_x)^2 + (A_y - B_y)^2} \tag{3.4}$$

$$EuclideanDistance_{(A',B')} = \sqrt{(A'_x - B'_x)^2 + (A'_y - B'_y)^2} \tag{3.5}$$

$$SubtractofEuclideanDistance_{(AandB \quad VS \quad A'andB')} = Eq.\ 3.4 - Eq.\ 3.5 \tag{3.6}$$

$$\theta_1 = tan^{-1}(\frac{A_x - B_x}{A_y - B_y}), \qquad \theta_2 = tan^{-1}(\frac{A'_x - B'_x}{A'_y - B'_y}) \tag{3.7}$$

As indicated in Figure 3.10, x refers to the vertical axis and y refers to the horizontal axis.

$$Direction_{(sub-region_{AandB}, sub-region_{A'andB'})} = |\theta_2 - \theta_1| \tag{3.8}$$

Equation 3.6 computes the subtract of the distance and Equation 3.8 computes the direction difference between the two sub-regions *A and B* versus *A' and B'* in

query and registered fingerprints. If the Equation 3.6 and 3.8 are of small value, it reflects that the two sub-regions *A' and B'* are consistent (in location) with the two sub-regions *A and B* which makes the information provided by A more reliable. If Euclidean distance and direction difference for each pair of sub-regions is smaller than the $Threshold1$ and $Threshold2$ respectively, the pair of sub-regions are considered consistent. $Threshold1$ is set to 20 pixels and $Threshold2$ is set to 25 degree.The ranking assigned to $sub-regions_A$ is based on the portion of the other sub-regions that pass the above condition (showing distance and direction less than $Threshold1$ and $Threshold2$). Ranking based on the passed portions of the other sub-regions makes the ranking strategy flexible in the case of partial fingerprinting as the number of other available sub-regions may vary. Thus the ranking assigned to $sub-regions_A$ is as follows:

$$Rank_{(sub-region_A)} = S_A + S_A \times (N_A/AS_A) \tag{3.9}$$

where S_A represents the similarity (correlation value), N_A represents the number of consistent sub-regions and AS_A represents the number of available sub-regions. However, in addition to the *number* of other available sub-regions, their *size* also need to be considered in the ranking. As mentioned in Section 3.3.1, the query image is decomposed into sub-regions of different sizes. Due to the intra-class variation and image distortion, sub-regions of bigger size have less chance in finding the match in the registered fingerprint and result in a high similarity value. Thus the ranking is compensated for taking care of the sub-region sizes as:

$$Rank_{(sub-region_i)} = S_i + S_i \times (N_i/AS_i) \times SW_i \tag{3.10}$$

where SW_i represents the weight assigned to sub-regions according to their size. The bigger the sub-region size is, the bigger weight is assigned to it.

After ranking each sub-region according to the Equation 3.10, the rotational difference of the two fingerprints is detected based on the angle value (Table 3.1) provided by the sub-region that has the highest ranking.

3.3.4 Performance evaluation of the alignment

Figure 3.11 shows the ROC curve of the alignment method described in Section 3.2 compared with alignment method in Section 3.3. The comparison is made on the FVC 2002_DB1 dataset where both registered and query fingerprints have at least one common pair of singular points. The alignment by only using the fingerprint ridge (indicated by the red curve, $EER = 1.28\%$) performs slightly better compared to using singular points for coarse alignment (indicated by the black curve, $EER = 1.62\%$). The improvement achieved is through the ranking process mentioned in Section 3.3.3 which took into account other available regions in fingerprints in order to increase the reliability of finding the rotation difference of the two fingerprints. However, when accuracy is not the main focus of the system, using the singular points (if available) is reasonable due to the faster process of aligning the fingerprints in this case.

Both the query and registered fingerprints went through the alignment process and the information obtained at this stage can represent the characteristics of the two fingerprints that needed to be aligned (as being an intra or inter comparison). If the registered and query fingerprints are from the same finger (intra comparison), there are more sub-regions with higher ranked values compared to inter comparisons. Therefore, in the next section, how this information can be used by a classifier to recognise whether the two fingerprints are from the same finger or not is discussed.

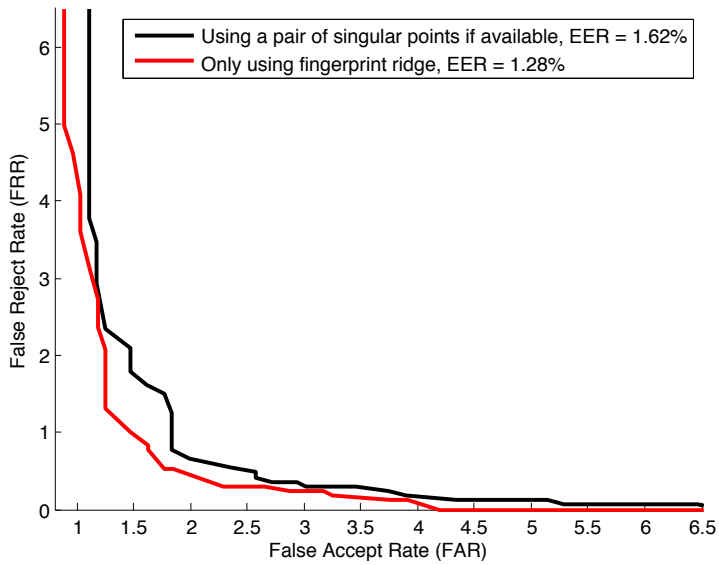


Figure 3.11: ROC of the two proposed alignment methods

3.4 Recognising the Fingerprints Using the Obtained Information

The alignment described in Section 3.3 and ranking of sub-regions according to the other sub-regions (Section 3.3.3) provides useful information that can be used to recognise fingerprints with no need to detect common regions and compute local and global similarities. Recognizing fingerprints at this stage will improve system efficiency since many of the comparisons can be recognised to be from the same finger (genuine user) or not (imposter user) without any further processing.

As shown in Figure 3.8, every sub-region in the query fingerprint is rotated from -35 to $+35$ degrees. For each angle, the highest ranking of $sub-region_i, \quad i = 1, ..., n \quad n = numberofsub-regions$ according to Equation 3.10 is recorded which provides 70 values. These 70 values are fed into the Neural Network classifier as the input features. The output of the classifier indicates whether the input features are obtained from an intra or inter comparison. However, as it is discussed

in more detail in Section 3.5, the output is a value, showing the probability of input feature being an intra or inter comparison.

3.4.1 Training the classifier

To train the neural network, 199 comparisons (100 intra and 99 inter comparisons) are used which is almost 2.5% of the FVC2002_DB1 dataset. Figure 3.12a shows the distribution of intra and inter cases in the training sample for angles from -35 to $+35$. The x-axis shows the angle value (from -35 to $+35$) and y-axis shows the highest ranking value obtained from Equation 3.10. Inter and intra cases are shown by red and blue lines respectively. This distribution shows that the rotation difference between most of the fingerprints in the training sample is -10 to $+10$ degree. As in other cases the rotation difference may vary from this and also to be able to train the classifier independent from the angle, the 70 input features are sorted. As can be seen in Figure 3.12b, most of the intra cases have higher values compared to inter cases. These input features are sorted in the test set as well to make it similar to the behaviour of the training sample which is now just based on the values not the angles.

3.4.2 Testing the classifier

After training the classifier by the information gathered from comparing intra and inter cases, the classifier is used to classify whether a comparison is an intra or inter fingerprints (two fingerprints belong to the same finger or not). Thus, same as in training, the 70 features of a comparison are sorted and fed to the classifier. As Figure 3.12d shows, by sorting the features, the intra and inter comparisons represent roughly the same ranked similarity score in many cases as the trained set. Moreover, Figure 3.12c shows that the highest ranked similarity score in the testing set may be achieved by any angle (not only between -10 and $+10$ like in the

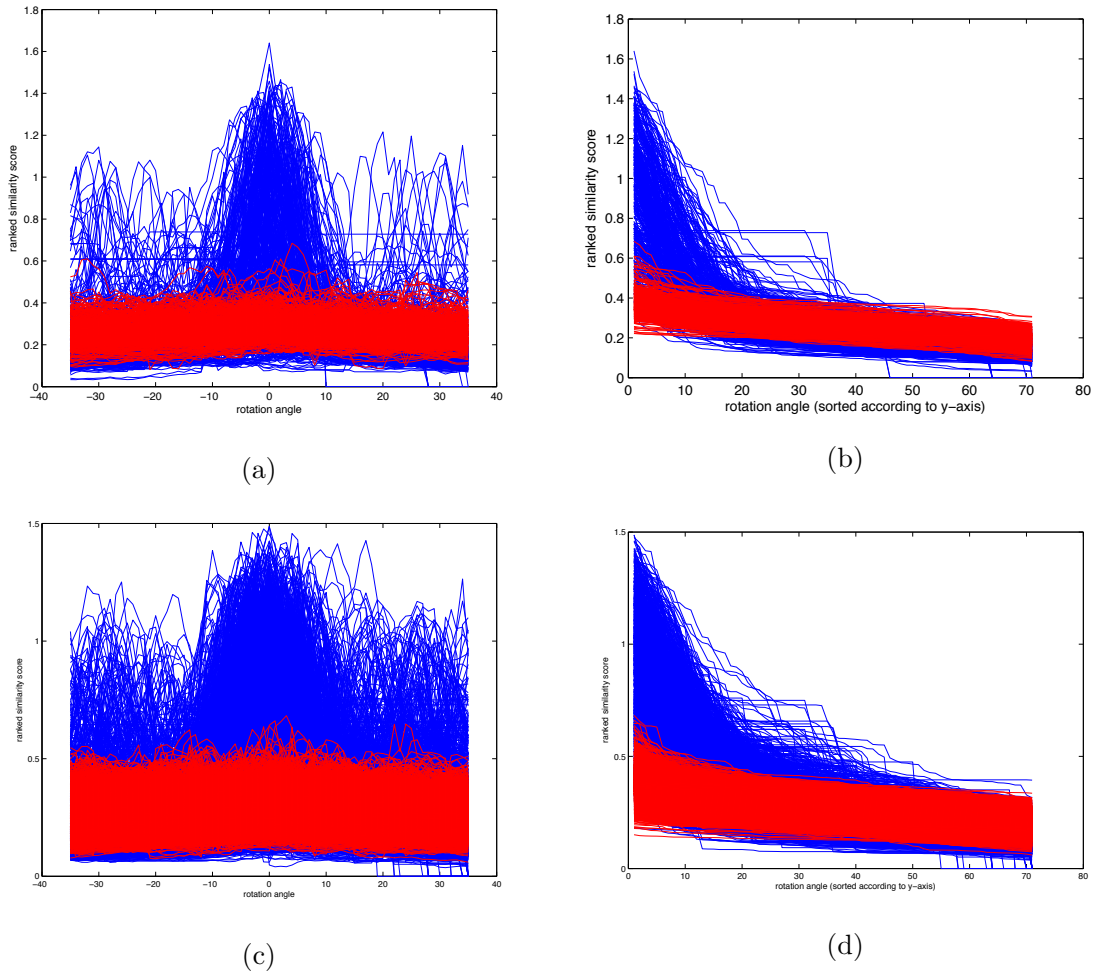


Figure 3.12: Plot of ranked similarity score in different rotation angles from -35 to +35 (total of 70 features). Blue and red lines indicate intra and inter cases respectively. a) training set distribution, c) test set distribution, b) and d) sorted train set and test set respectively according to the ranked similarity score.

training set; Figure 3.12a) which highlights the necessity of sorting the features.

3.5 Experimental Results

The Neural Network classifier employed is part of the Neural Network Toolbox in Matlab. According to this Neural Network toolbox release note [125]:

"The Neural Network classifier returns networks that use the Soft Max transfer function for the output layer instead which results in output vectors normalized so

Table 3.3: Result of Neural Network classifier for two intra and two inter comparisons.

Actual Class / Probability to be an ...	Intra-1	Intra-2	Inter-1	Inter-2
intra comparison	0.82	0.45	0.1	0.38
inter comparison	0.18	0.55	0.9	0.62

they sum to 1.0, that can be interpreted as ***class probabilities****."*

According to the above statement, only comparisons that the Neural Network classifies with a high probability are identified to be an intra or inter comparison during the first level of the recognition system. For instance, Table 3.3 shows the result of the classifier for two intra and two inter comparisons. When the features for the first intra comparison (Intra-1) and first inter comparison (Inter-1) are given to the classifier, the probability of correctly identifying them (as intra or inter) is about two times higher than in Intra-2 and Inter-2. This indicates either the Intra-2 and Inter-2 are intra fingerprints with high variation and inter fingerprints with high similarity or the information extracted so far (the features) do not provide adequate properties to reliably recognise them. Therefore, at this stage, the result of the classifier is only considered when a comparison is recognised to be intra or inter with high probability. The rest of the cases are processed in the second level of matching (Chapter 4). As shown in Table 3.4, By only considering cases with a probability of higher than 0.97, 3673 out of 7551 cases in the testing set can be recognised with 98.5% accuracy. Although the accuracy of matching can be improved by considering only the cases with a higher probability than 0.971, (0.971) is the best trade-off (in terms of accuracy) to split the test set between the first and second level of matching.

Also, in order to measure the effectiveness of using Neural Network classifier compared with a linear divider based on the ranked values for sub-regions, the following experiment is conducted:

Table 3.4: Recognising intra or inter comparisons with a Neural Network Classifier when they can be recognised with a high degree of certainty.

Cases with probability above	0.787	0.899	0.971	0.982	0.996
Accuracy (%)	94.34	96.28	98.50	99.03	99.64
Error Rate (100 - Accuracy) (%)	5.66	3.72	1.5	0.97	0.36
Number of cases processed	6532	5720	3673	2582	277
Total number of cases	7551	7551	7551	7551	7551

Table 3.5: Comparison of the Neural Network classifier with threshold-based recognition of fingerprints based on the information provided through the alignment stage in terms of accuracy.

Cases with probability above	0.787	0.899	0.971	0.982	0.996
Number of cases processed	6532	5720	3673	2582	277
Total number of cases	7551	7551	7551	7551	7551
	Accuracy (%)				
NN classifier	94.34	96.28	98.50	99.03	99.64
the highest rank	87.96	89.29	94.38	96.16	98.32
average of rank values	67.01	68.30	73.91	75.44	96.38
average of 20 highest rank values	74.58	76.94	84.59	84.35	97.83

As mentioned in Section 3.4, 70 ranked values are computed for a pair of fingerprint that are going to be aligned. The angle that the sub-region with the highest rank was rotated by, is used to indicate the rotation difference between the two fingerprints since this sub-region showed more consistency with respect to the global structure of the fingerprint (Section 3.3.3). Table 3.5 shows the result of using threshold based matching according to the the ranked values to differentiate a comparison to be intra or inter. When the highest ranked value is used as the *matching score* of the comparison, the accuracy achieved is close but less than the accuracy of the classifier. However, when the average of all the ranked values (70 ranked values) is used the accuracy drops significantly. According to Figure 3.12d, the ranked values for inter and intra cases are different for the first highest 20 ranked values. By averaging only these 20 highest rank values, the achieved accuracy improves compared to averaging all the 70 values but is still lower than the accuracy of the classifier.

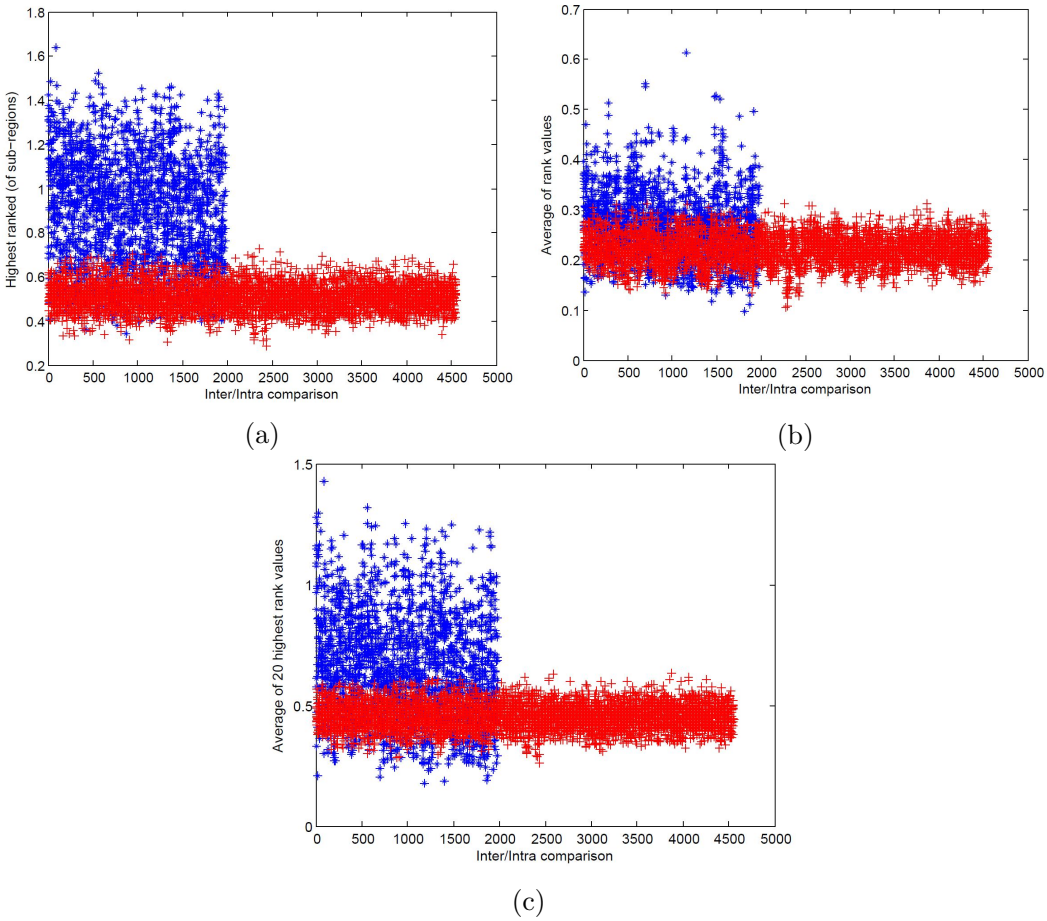


Figure 3.13: a) Plot of highest rank distribution. b) Plot of averaging the rank values. c) Plot of averaging the highest 20 rank values. Blue and Red indicate an intra and inter comparison respectively.

The distribution of these three cases are shown in Figure 3.13a, Figure 3.13b and Figure 3.13c respectively. As shown in Figure 3.13a, there are less intra and inter comparisons that their *matching score* overlaps compared to Figure 3.13b and Figure 3.13c, resulting in higher accuracy.

When the average of all the 70 values are used as the matching score of a comparison, the values in the right side of the plot in Figure 3.12d that are very close to each other for inter and intra cases reduce the average value for intra cases. In all cases, the accuracy of using the Neural Network classifier is higher than the threshold-based matching due to using all the information obtained by

the sub-regions.

In a nutshell, using the Neural Network classifier to recognise whether a pair of fingerprints are inter or intra based on the information provided in Section 3.3.3, improves the efficiency of matching since there is no need for further processing these pairs. At the same time, the classifier shows higher accuracy compared to the threshold-based system that uses the highest or average of the ranked values obtained in Section 3.3.3. As mentioned in Section 2.9, in order to compare the experimental result of this phase, other data manipulation techniques need to be performed. Therefore, the comparison of the results of the proposed system with other works is mentioned in Chapter 5 after all the required steps are performed .

However, cases that are not processed in level one matching, can go through the second level of matching. As part of the second level matching, the common regions between the two fingerprints need to be identified. That increases the efficiency of matching as the sub-regions only need to be compared with the corresponding regions on the other fingerprint (due to alignment) not the whole fingerprint. It also increases the reliability of the similarity values obtained from each region as it lowers the probability of mis-overlapping the query sub-region on the registered fingerprint.

3.6 Common Region Extraction

Local matching techniques are proposed to overcome the problems such as lack of robustness with respect to the non-linear distortion in global matching techniques [79]. In order to locally match the fingerprints, they are decomposed into smaller regions. The main reasons that the local matching techniques perform better than the global ones are: First, their capability in handling the non-linear distortion of the fingerprints. Second, the effect of the distorted regions on the final similarity degree is reduced by dividing the images into smaller regions.

With regard to the size of the smaller regions (as discussed in Section 3.3.1), in computing the correlation of two images, there is a trade-off between size of the region and sensitivity to distortion. Considering the resolution of the fingerprints in the dataset (FVC2002 DB1), it is observed that the minimum region size required for any feature to be extracted is approximately 45×45 pixels. Moreover, this size is also used to extract the common regions between the two fingerprints.

Common region extraction is performed after the fingerprints are aligned. Two methods are proposed to extract the common regions for each one of the alignment methods proposed in Section 3.2 and Section 3.3. The first method (Section 3.6.1) uses a pair of common reference points available in both registered and query fingerprints. Although reference points are level-1 features that are reasonably reliable (as generally they are not significantly affected by intra-class variations), their existence cannot be guaranteed in partial fingerprints. Thus, in the second method (Section 3.6.2), the information provided by fingerprint regions from Section (3.3) is used to extract the common regions. In the second method, there is no need for reference points and as long as part of the fingerprint is available, the common regions can be identified.

3.6.1 Based on reference points

In order to extract the common regions, at least one common reference point needs to be located on both fingerprints. The query fingerprint is projected on to the registered fingerprint by aligning their common reference points. Subsequently, the overlapping regions are identified as the common regions between the two fingerprints. An important advantage of extracting common regions via this strategy is the reduction of the search space which improves the system efficiency. As mentioned in Section 3.2, to handle the translation difference between two fingerprints, the sliding windows technique is applied (each region from the query fingerprint is

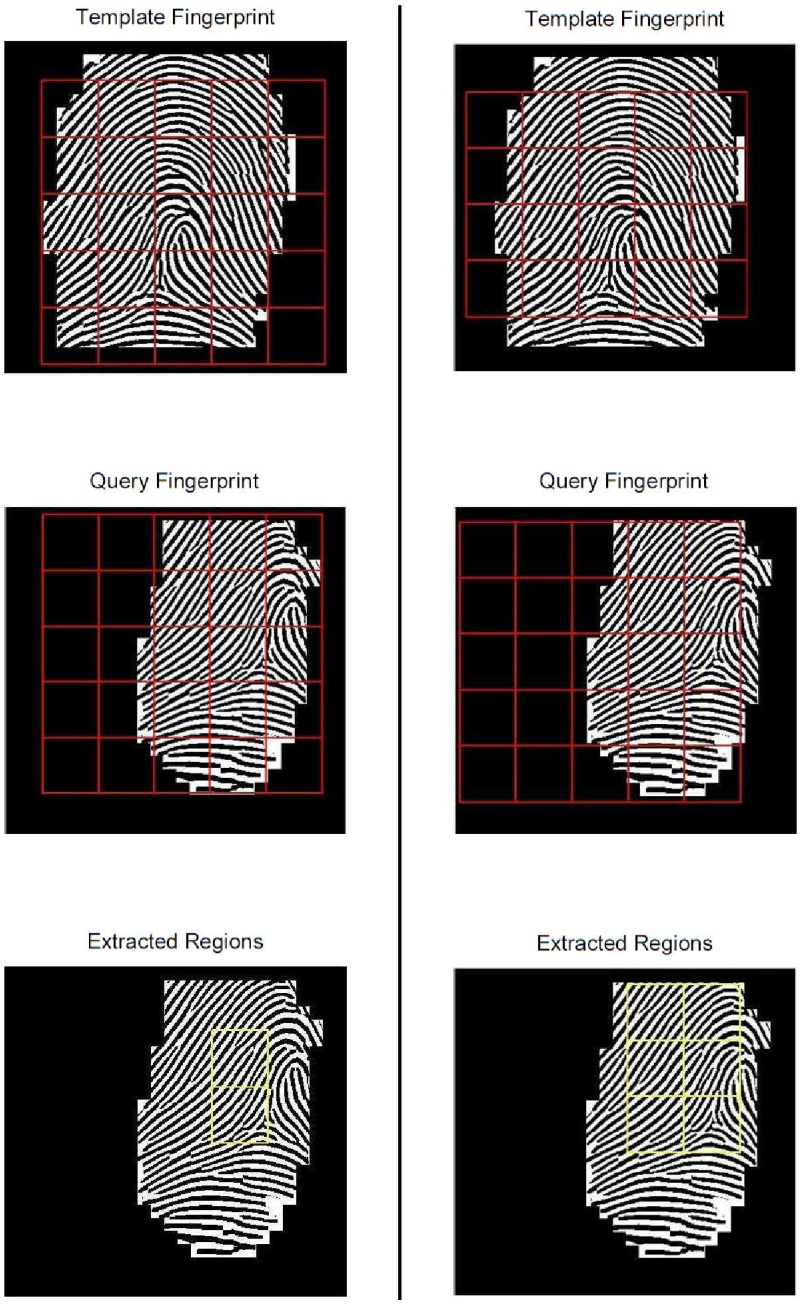


Figure 3.14: An example of extracting valid common regions by using different reference points as the centre of the grid.

compared with all the other regions of the registered fingerprints). If the size of the one image is way greater than the other one, this could be a very time consuming process. Therefore, identifying the same regions on both fingerprints will reduce the search space and improves the system efficiency.

In addition, the location of the singular point is set as the centre of the region containing it. The other regions are located next to the previous one in such a way that every pixel on the fingerprint is covered. However, due to the fingerprint segmentation (separating fingerprint foreground from background), the regions close to the border are usually missed since only regions that contain fingerprint information is considered as a valid region. Therefore, in order to get the maximum common regions, the location of the first region is changed from $-\frac{RegionSize}{2}$ pixels to $+\frac{RegionSize}{2}$ pixels. Also if more than one singular point is available, the same strategy is used for each one of them. Finally the maximum common regions between the two fingerprints could be extracted. An example of extracting the common regions between a query and template fingerprint is shown in Figure 3.14. On the left side, the core point is considered as the centre of the grid and only two valid regions are identified as common regions. On the right side, the delta point position is determined as the centre of the grid with six valid regions extracted as common regions.

3.6.2 Based on Fingerprint regions

To extract the common region between the two fingerprints in order to perform the local matching comparison, the location of fingerprint reference points was used in previous Section and also in [126] and [127]. However, the limitation of this method in extracting the common regions (existence of the reference points in fingerprint; considering the partiality of available information in partial fingerprint) is overcome in this method. The common/corresponding regions of the 2-dimensional fingerprints could be detected by determining an off-set point. The alignment (in [126] and [127]) was done by cropping a region from the query fingerprint and *rotating* and *sliding* that region with respect to the registered fingerprint to find their rotational difference. However, based on the ranking strategy mentioned in

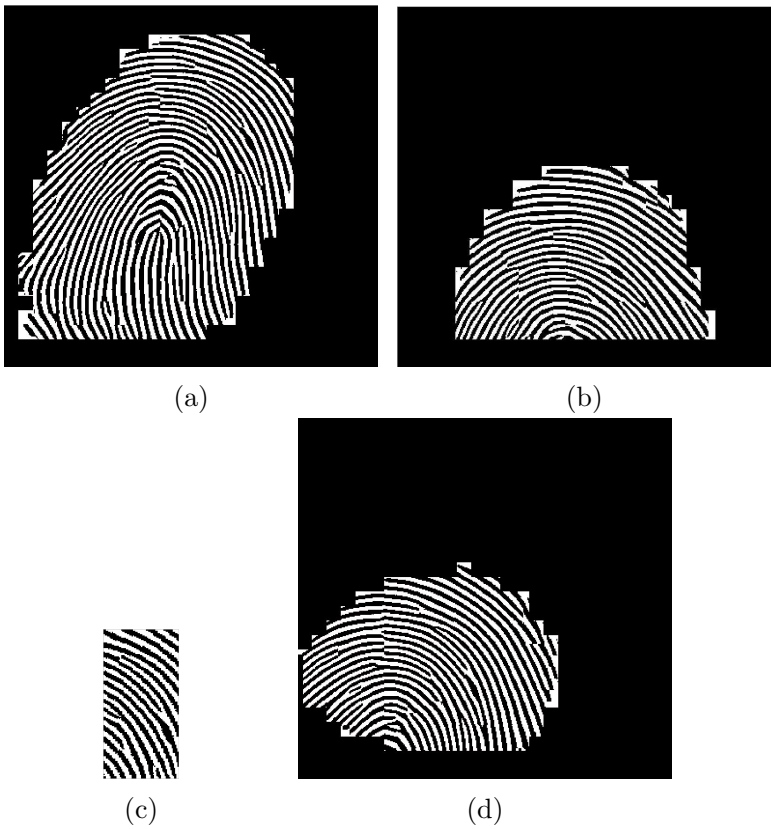


Figure 3.15: a) Registered fingerprint, b) Query fingerprint, c) Region on query fingerprint used for alignment and common region extraction, d) Query fingerprint after alignment.

Section 3.3.3, the most reliable sub-region is selected and the *location* of the overlapping region with the maximum similarity among the other regions is used as the off-set to detect the corresponding regions. Identifying the corresponding regions in this manner overcomes the translation difference in the two images. In addition to not being dependent on reference points to detect the corresponding regions, it is very applicable in the case of partial fingerprint matching since a small region is enough to complete the process of alignment and common region extraction.

Figure 3.15 shows an example of two registered and query fingerprints aligned by the alignment method presented in Section 3.3. Figure *c* shows the region from the query fingerprint that is used for overlapping on the registered image to find the rotation difference and be used as the *off-set for common region extraction*. This

Table 3.6: Normalized cross correlation values of overlapping Figure 3.15 *c* on Figure 3.15 *a*.

row \ column	224	254	267	279	294
168	-0.0249	-0.1162	0.2028	0.0380	0.0986
185	-0.0116	-0.0080	0.7148	0.0926	0.0578
188	-0.0381	-0.3003	0.0890	0.1195	0.0491
208	-0.0552	0	0.0470	0.0448	0.0162

region is cropped after the query fingerprint is rotated by -28 degree (rotational difference of the two images is -28 degrees). Table 3.6 shows the Normalized Cross Correlation (NCC) values of overlapping Figure *c* on Figure *a*. Due to the sliding windows technique, the NCC of overlapping of these two regions can be computed for every pixel. Some of these values as well as the location that gives the highest value are represented. Row 185, column 267 is the (x, y) location on the registered image from which the cropped region from the query fingerprint produces the highest correlation. Thus, this location on the registered fingerprint as well as the location where Figure *c* is cropped from the query fingerprint are used as the off-set to detect the corresponding regions. Corresponding regions are identified based on the distance of each region on the registered and query fingerprint to the off-set point. Assume Figure *c* is cropped from (x', y') location in query fingerprint. If there is a valid region (occupied with fingerprint information and fulfilling the quality requirement mentioned in Section 2.5.2) with the same size available in both the query and registered fingerprint with respect to the (x', y') location, these two regions are considered to be corresponding regions.

3.7 Conclusion

In this Chapter, the alignment and common region extraction phases of the proposed partial fingerprint matching method is introduced. Alignment is one the most important phases in region-based approaches as in a region-based compar-

ison, the regions are compared in a pixel wise manner and rotationally different (intra) fingerprints may be mis-recognized due to this. To align the fingerprints two methods are proposed, of which the second method performs better with the improvement reported and analysed.

The information obtained through alignment, was used not only to recognise the fingerprints (as the first level of matching), but also to detect and identify their common regions. Recognising the fingerprints with a high degree of confidence at this stage, not only reduces the complexity of going through the second level matching for each individual case, but also recognises a large portion (almost 50%) of the dataset with almost 98.5% accuracy.

To extract the common regions, the reference points location was used as an offset. However, due to the uncertainty in the availability of reference points in partial fingerprint, and also reliable information that could be obtained through ranking strategy, the location of the sub-region with highest ranking was used as the offset point.

The next Chapter discusses how the similarity of a pair of fingerprints is computed. This similarity value is considered as the matching score of the two fingerprints from which the system makes a match or non-match decision accordingly. The matching score is computed in two stages: locally and globally. As a prerequisite to computing the local similarities, the fingerprints are aligned and their common regions are identified at this stage. Computing the similarity locally introduces the advantage of lowering the effect of distorted regions on the final similarity value in turn, this compensates for compensating for non-linear distortion which might not allow for the perfect alignment of fingerprints and etc. After computing the local similarities, a single value representing the final matching score of a pair of fingerprint is computed by applying global consolidation techniques.

Chapter 4

Computing the Similarity Score

4.1 Preamble

This chapter discusses the second objective of this research on how to compute the similarity/matching score of a pair of fingerprints specifically when fingerprints are partial. The result achieved through the similarity measurement in this chapter (as the final stage of matching a pair of fingerprint) is compared with other works in the Chapter 5.

The similarity of fingerprints is computed after fingerprints are aligned and their common regions identified. Due to the small overlap of partial query fingerprint with the registered fingerprint, determining the similarity score can be very challenging. We need a similarity score measurement that can take into account this small overlap resulting from partial fingerprint matching. As discussed in Chapter 2, the correlation coefficient of two fingerprints reflects all the available features. Therefore, the similarity of two fingerprints is computed in terms of their correlation coefficient. In addition, as discussed in Section 1.2 and Section 2.4, the fingerprints could suffer from distortion. The distortion of a fingerprint may not be uniformly distributed and different regions may have different image quality levels. Thus, computing the similarity of the fingerprints locally (sub-regions extracted

in Section 3.6) reduces the effect of the distorted regions on the overall similarity score. As a consequence, considering the quality of sub-regions can result in better discrimination between inter and intra cases. Two intra fingerprints (with low intra-class variation) should have high correlation in every block and vice versa for inter fingerprints. However, one of the main reasons that intra fingerprints result in low similarity is that some parts of the fingerprints are distorted. Therefore, identifying the low quality blocks and reducing their effect on the final similarity helps to increase the similarity of intra cases and reducing the probability of falsely rejecting them. On the other hand, by so doing, the final similarity of inter cases will not be affected significantly since the low similarity in inter cases are mainly due to the difference between ridges and valleys structure of the two fingerprints not their quality.

The proposed partial fingerprint matching method is a region-based approach which compares the fingerprints in a pixel-wise manner. Therefore, to compute the similarity of the two fingerprints locally, their corresponding regions need to be identified and compared to each other. To identify the corresponding regions, the fingerprints need to be rotationally aligned as discussed in Chapter 3.

In addition to identifying the most suitable approach for partial fingerprint matching (region-based, as discussed in Chapter 2), how regions are processed is also an important step in fingerprint matching. Cappelli et al. in [79] claimed that in recent decades local matching has addressed the weaknesses in global matching such as high computational complexity and lack of robustness with respect to non-linear distortion. In the next section, how local similarities are computed and why they tolerate the effect of distorted regions on the fingerprint similarity score is discussed. Additionally, the global similarity score is computed for comparison, by consolidating local similarities. The selected local similarities through global consolidation techniques are then averaged by different averaging techniques. Fig-

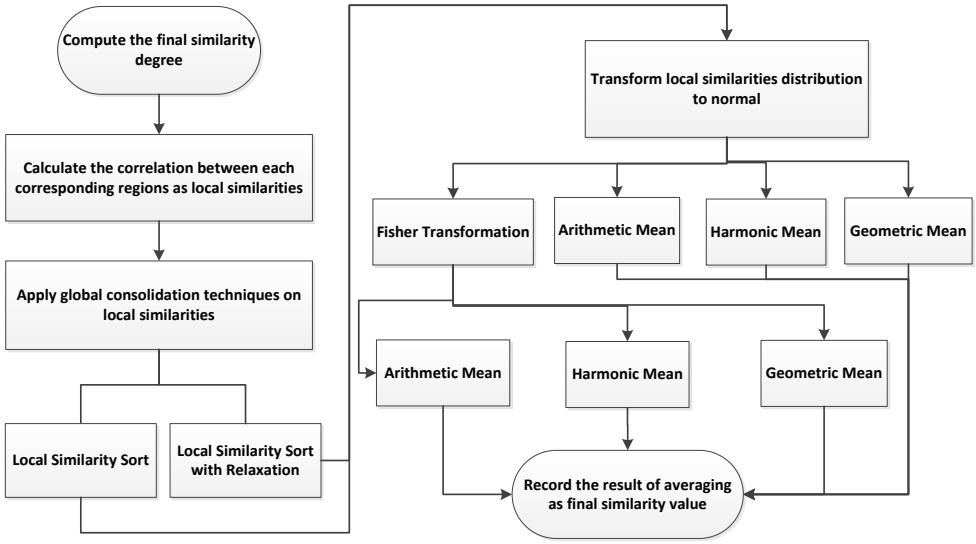


Figure 4.1: Block diagram of computing the final similarity score of two fingerprints.

ure 4.1 shows the block diagram of computing the final similarity and the details of each step is presented in the next sections.

4.2 Local Similarity Scores

Conventionally, in correlation-based methods, the whole fingerprint is considered as one big *single-region*. Accordingly, the similarity score was computed based on the correlation of the two single-regions. In order to lower the effect of distorted regions on fingerprints, the similarity of two fingerprints is computed locally (at a small regional level) and the average value of local similarities is considered as the final similarity score between the two fingerprints (refer to Section 4.3 for more details on computing global similarity). Computing the similarities of each pair of small-regions individually and then averaging them to obtain the global similarity is a robust and reliable technique for fingerprint matching since the final similarity score could be computed by considering the same contribution to

each of the local similarities. By so doing, the distorted regions are taken into account as individual local similarity values and it does not affect the similarity of other regions. Hence, in our method, local similarities are computed based on the Normalized Cross Correlation (NCC) of a pair of corresponding regions (refer to Chapter 2 for details of superiority of NCC compared to other metrics). The NCC of 2-dimensional images (the two corresponding sub-regions) f and t is calculated as (aka Pearson's r correlation) [99]:

$$NCC = \frac{1}{n} \sum_{x,y} \frac{(f(x,y) - \bar{f})(t(x,y) - \bar{t})}{\sigma_f \sigma_t}, \tag{4.1}$$

where $\bar{f}$ and $\bar{t}$ are the mean and σ_f and σ_t are the standard deviation of the images f and t respectively and n is the number of pixels of the images. x and y represent the coordinates of the pixels in the two dimensional f and t fingerprints.

However, common regions between registered and query fingerprint are not always detected completely accurately due to the following three reasons. **First**, detecting the common region according to Section 3.6, requires the precise location of the reference points as the common regions are identified based on the position of the common reference point. However, the reference points are not always precisely located. Therefore, the detected common regions based on the location of these points are also not always precisely located. **Second**, even if the reference points are located precisely, it is still very challenging to precisely locate the corresponding regions due to intra-class variation and non-linear distortion. **Third**, although the accuracy of detecting common regions has improved through Section 3.6.2 by considering other sub-regions in the query fingerprint, it still is not foolproof. Therefore, the corresponding region of the registered fingerprint needs to be larger than the one in the query image to compensate for small errors in computing the exact location of the corresponding regions. Furthermore, to make sure that even small rotational differences between query and template fingerprints (after

aligning the fingerprints) is taken care of, the correlation of the two corresponding regions is computed by rotating the sub-region of the query fingerprint by $\pm 5°$. Considering the mentioned two points (a larger sub-region of registered fingerprint and rotating the query sub-region by $\pm 5°$), the problem of non-linear distortion can be reasonably accounted for as it is caused due to finger skin elasticity.

After the local similarities are computed, a particular value (a global score) needs to be obtained from the local similarities to indicate their overall similarity score [79]. To obtain the final similarity score between the two fingerprints (global score/similarity), the local similarities are further processed by averaging methods and global consolidation techniques.

4.3 Global/Final Similarity Score

Consolidating the results of local matching into a single value representing the global/final similarity of the fingerprints is challenging since it could highly affect the system performance. Cappelli et al. [79] introduced four global score consolidation techniques inspired by ideas already in the literature.

Further to the global consolidation technique proposed by Cappelli et al., one of the widely-used techniques is averaging the local similarities by computing the arithmetic mean. However, the other types of averaging might also lead to improving the recognition accuracy rate when combined with the global consolidation techniques. In the following sections, a discussion on the effect of different global similarity consolidation techniques and averaging methods is presented.

4.3.1 Global Similarity consolidation Methods

Cappelli et al. [79] introduced four global consolidation techniques to represent the similarity of two fingerprints by one single value, based on their local similar-

ities. Although these techniques were used in minutiae-based matching it could also be extended to region-based matching with some changes. Local Similarity Assignment (LSA) and Local Similarity Assignment with Relaxation (LSA-R) are two of the techniques proposed by Cappelli et al. that are not applicable in our method. The major difference between the proposed method here and Cappelli et al.'s method (in terms of computing the final similarity) is that in the proposed method the common regions are identified and the result of comparing the corresponding regions is considered as a local similarity value. In Cappelli et al.'s method the similarity of each minutiae cylinder is computed with respect to all other cylinders. A minutiae cylinder is a 3D representation of minutiae (with a fixed distance) from a centre minutiae (refer to [79] for more details). LSA and LSA-R techniques search for the best match between minutiae points that could lead to the maximum local similarities which also compensates for the fingerprint alignment. The fingerprints are aligned in the proposed method which make these two techniques not applicable in this study.

In other words, the alignment can be performed by considering different rotations for each query sub-region and also common regions can be identified by comparing each query sub-region with all of the registered sub-regions. However, thanks to alignment and common region extraction as mentioned in Chapter 3, there is no such need to do so as the fingerprints are aligned and their corresponding regions are located in our proposed method.

Local Similarity Sort (LSS), sorts the similarity scores and selects the top n values (Section 4.3.1.1). In LSA, by using Hungarian algorithm [128], the regions are matched in a way that produces the maximum global score. In this case, the corresponding regions are identified in such a way that the average of the selected regions will produce the highest global score. LSS-R, was inspired by the relaxation approach proposed by Rosenfeld et al. [129] and recently applied to triangular

minutiae matching in 2006 [130]. In a minutiae-based method, the basic idea is to iteratively modify the local similarities according to their compatibility among minutiae relationships. In particular, the local similarity between two minutiae points (a, b) is strengthened if the global relationships among *a and b* and some other minutiae in the query and registered fingerprints are compatible, otherwise it is weakened (Section 4.3.1.2). Computing the final similarity score by LSA-R, is the same as LSS-R, but the regions are selected via the LSA technique.

4.3.1.1 Local Similarity Sort (LSS)

This technique sorts all the local similarities and selects the highest n similarities. Instead of selecting a constant n number of local similarities, the top k percent are selected. This provides more flexibility in partial fingerprint matching since the number of local similarities vary according to the available portion of the fingerprint area. This could also be applied by using all the available information by setting n to the maximum number of available local similarities. The global score is then calculated by averaging the corresponding local similarities (Section 4.3.2).

Local similarities are sorted by considering the quality of each sub-region in the query fingerprint and its pair in the registered fingerprint. The sorting is done according to the mean and standard deviation (std) of the quality of the sub-regions as:

$$QualityRank = \frac{mean(a, b)}{std(a, b)}, \tag{4.2}$$

where a and b are the quality of the sub-regions computed as in Section 2.5.2. According to this equation (4.2), the numerator and denominator make sure that if both regions a and b are of good quality, they will be assigned to a high quality rank. However, if one is of low quality, the standard deviation will be higher

which results in a lower quality rank. By sorting the local similarities according to Equation 4.2, local similarities that are obtained from the highest quality sub-regions are selected. This results in local similarities that are more reliable (refer to Section 3.3).

4.3.1.2 Local Similarity Sort with Relaxation (LSS-R)

In this technique (with some modification), if a local similarity is surrounded by regions producing higher similarity, then its score is strengthened. Here surrounding sub-regions are also of high quality, or the comparison is an intra case from which a larger sub-region with high similarity can be detected in both query and registered fingerprints. This technique is modified to be more flexible to the number of neighbouring regions due to the different number of local similarities as well as different number of neighbour regions on the borders. Like LSS, the selected similarities are then averaged. The different averaging methods are discussed in the next section.

4.3.2 Mathematical averaging methods

The concept of averaging is simple, but it is essential to know which average to use. Choosing the right averaging method enables correct estimation of the central tendency of the population. Central tendency refers to a single data point attempting to describe a whole set of data by representing the middle or centre of its distribution.

To analyse the effect of averaging, three different averaging methods (harmonic, geometric and arithmetic mean) are applied to calculate the global similarities from local similarities selected by LSS and LSS-R techniques. It should be mentioned that the other averaging methods such as median and mode are not considered in this study as median only represents one out of n local similarities and mode

represents the local similarity that appears most often in a set of local similarities. They both ignore large amount of the local similarities which does not suite the purpose of using all the available information.

The common merit between all these three means is that they all are calculated based on all the observations [131]. Thus, these three means meet the requirement of giving contribution to all the available information in the fingerprint. However, the main difference between these means is how they are affected by extreme values. Out of these three, geometric mean is the least one affected by data skew with arithmetic mean second least affected followed by harmonic mean [131]. It is essential to determine whether being affected by extreme values leads to better distinguishment of inter and intra fingerprints or not (refer to Section 4.4).

4.3.2.1 Arithmetic Mean

Arithmetic Mean (AM) is defined as sum of the data divided by the number of data in the set [131]:

$$A.M. = \frac{\sum_{x_i}}{n}, \qquad for \quad i = 1, 2, ...N \tag{4.3}$$

As stated by Agarwal [131] the merits and demerits of arithmetic mean are:

Merits:

1. Easy to calculate.
2. Rigidly defined.
3. Based on all data.
4. Data need not be sorted.
5. Less susceptible to sample fluctuation.

Demerits:

1. Significantly affected by extreme values.
2. Mostly does not correspond to any of the data.
3. Does not represent any information about the skew in data

As stated above, averaging the correlation values by arithmetic mean may be biased due to the skew in data distribution. The skew in data distribution in our method refers to low local similarities when the majority of local similarities are high and vice versa. Thus, to lower the effect of skewed local similarities the *Fisher transformation technique* [132] is applied to transform the data into an almost Gaussian *Probability Density Function* (PDF).

4.3.2.1.1 Fisher Transformation

Omid et al. in [127] investigated that Fisher transformation normalizes the distribution of Pearson's r correlation and can be used to obtain an average value that is less affected by distribution skew in fingerprint matching. The Fisher transformation is obtained as:

$$z_i = 0.5 \times ln(\frac{1 + r_i}{1 - r_i}), \tag{4.4}$$

where r_i is the local similarity. The global similarity score is then computed by taking the mean value of z_i (as transformed values). After averaging, an inverse of Fisher transform is applied to normalize the mean value of r_i's for the global similarity score of the two fingerprints to be in range of $(-1, +1)$. The inverse transformation is achieved by:

$$\bar{r} = \frac{e^{2\bar{z}} - 1}{e^{2\bar{z}} + 1}, \tag{4.5}$$

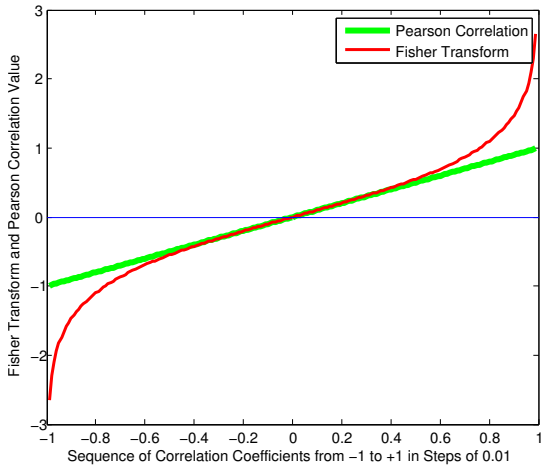


Figure 4.2: The transformation of the Pearson Correlation (green line) by Fisher Transform Technique (red curve)

4.3.2.1.2 Skew in data distribution

The skew of correlation values occurs due to the intra-class variation and inter-class similarity of fingerprints. In the proposed *region-based* method, the intra-class variation and inter-class similarity can be referred to as low local similarities in intra comparisons and high local similarity in inter comparisons. Since the effort is to match as many pixels as possible between two regions, most of the local similarities are positive numbers (especially in intra cases). Figure 4.2 shows the correlation coefficient (ranges from -1 to $+1$) and their corresponding value after being transformed by Fisher's technique (ranges from $-\infty$ to $+\infty$). As shown, if the correlation coefficient is greater than zero, the value is increased after transformation. Therefore, averaging the transformed data (global score before inverse transformation is applied) is higher than the average of the correlation coefficients. This is desired since it can reduce the effect of distorted regions on the final global score of matching. In other words, if only a few regions are distorted on a fingerprint, low correlation coefficients will be obtained as their local similarities will be normalized.

In case of an intra comparison, most of the correlation values for a pair of

corresponding regions (local similarities) indicate high similarity while a few of them indicate low similarity. It is likely that this comparison will be falsely rejected if the average of local similarities are used as the global score. However, by applying Fisher's transformation technique, the global score is higher than normal averaging. This is desirable since a higher global score is obtained compared to averaging the correlation values. To sum up, the merits and demerits of Fisher transformation are as follows:

Merits:

1. Easy to calculate.
2. Rigidly defined.
3. Based on all data.
4. Data need not be sorted.
5. Lowering the skew of data.
6. Provides less biased average.

Demerits:

1. Additional calculation to the averaging method.
2. Mostly does not correspond to any of the data.

4.3.2.2 Geometric Mean

Geometric mean is the nth root of products of n values of a set of observations [131]:

$$G.M. = (\prod_{x_i})^{\frac{1}{n}}, \qquad for \quad i = 1, 2, ...N \tag{4.6}$$

Merits:

1. Least affected by extreme values.
2. Based on all data.

Demerits:

1. Calculation is complicated.
2. Cannot be computed if any of the data is zero.
3. Is not calculable if more of the data are negative.

4.3.2.3 Harmonic Mean

Harmonic Mean (HM) is defined as the inverse of the arithmetic mean of the reciprocals of the observation of a set [131]:

$$H.M. = \frac{n}{\sum \frac{1}{x_i}}, \qquad for \quad i = 1, 2, ...N \tag{4.7}$$

Merits:

1. Based on all data.
2. Good mean for highly variable data.

Demerits:

1. Calculation is more complicated than arithmetic mean and geometric mean.
2. Is not calculable if any of the data is zero.
3. Mostly does not correspond to any of the data.

4.3.3 Local similarity distribution

Figure 4.3 represents the probability density function obtained by applying Fisher transformation on NCC values as local similarities. As shown, most of the intra-

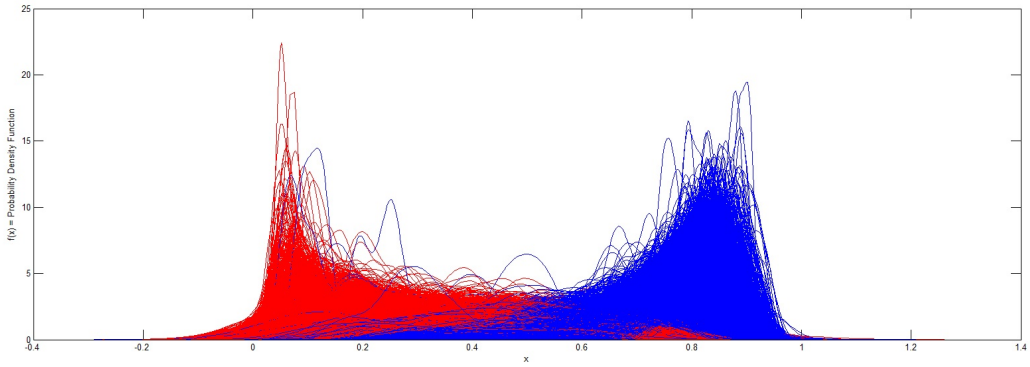


Figure 4.3: Probability Density Functions of local similarities for intra (in blue) and inter (in red) comparisons. x-axis and y-axis show the local similarities and PDFs respectively

cases have local similarities higher than inter-cases. However, it is not happening all the time and in some cases (as shown in Figure 4.4) local similarities in intra-cases have values lower than inter-cases due to high intra class variation in these cases. Also, intra-cases in Figure 4.4 do not show a normal distribution contrary to what inter-cases represent. The non-normal distribution of local similarities in intra-cases are caused due to: not perfectly aligning the fingerprints (and consequently mis-identifying the common regions), highly distorted regions in parts of the fingerprints (getting more low local similarities), etc. However, transforming the local similarities distribution to normal is a promising approach as it assigns the local similarities of intra-cases a bigger average value when there are more than one peak in local similarities distribution in intra-cases. Inter-cases have an almost normal distribution and will not change significantly through data transformation to normal.

4.3.3.1 Transforming local similarities distribution to normal

Box and Cox [133] presented a method that transforms non-normally distributed data to a set of data that has an approximately normal distribution. The Box-Cox transformation of x is defined as:

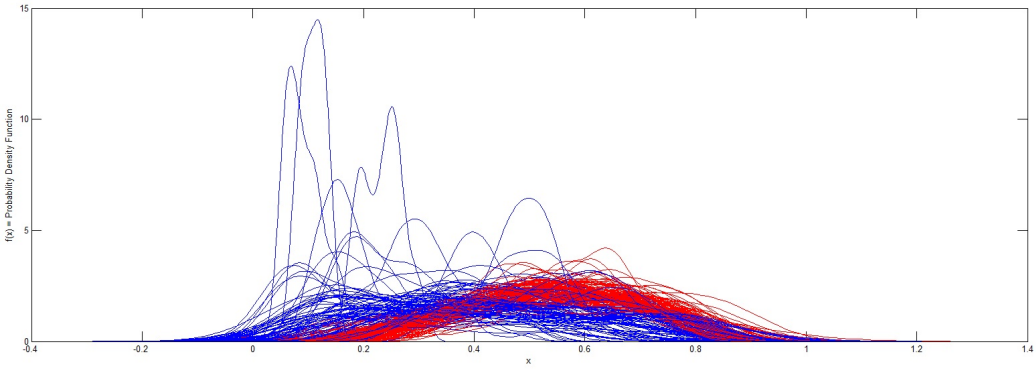


Figure 4.4: Probability Density Function of local similarities for intra (in blue) and inter (in red) comparisons which are *mis-matched*.

$$x' = \begin{cases} \frac{x^{\lambda}-1}{\lambda}, & \text{if } \lambda \neq 0. \\ log(x), & \text{otherwise.} \end{cases} \tag{4.8}$$

where λ is the power to which all data should be raised in order to maximize the Log-likelihood function in the data. In order to find the best value of λ, the Box-Cox power transformation searches from $\lambda = -5$ to $\lambda = +5$ until the best value is found. Each set of local similarities (for each intra/inter comparison) are transformed to a normal distribution using this technique.

The next section discusses the experimental results of the proposed similarity measurement method in order to evaluate the mentioned different strategies to compute the similarity/matching score between the two fingerprints. In a nutshell, the similarity of two fingerprints is computed in two steps (local and global). Local similarities are computed by measuring the normalized cross correlation of the two corresponding sub-regions between the two fingerprints. Measuring the similarity of fingerprints in this manner has the advantage of lowering the effect of distorted regions on final matching/similarity score of two fingerprints (Section 4.2) as well as providing the opportunity to process the local similarities further through global consolidation techniques. Two global consolidation techniques

were discussed in Section 4.3. The local similarities processed through global consolidation techniques are then averaged by different averaging techniques. The merits and demerits of each averaging technique were discussed. Fisher transformation is applied in order to lower the skew in local similarities and provide a set of local similarities that are less affected by extreme values. To further lower the skew in local similarities they are transformed to a normal distribution by applying the Box and Cox technique. The block diagram of the proposed similarity measurement was presented in Figure 4.1. The result of each different strategy is presented in the next section which provides the best setting (of averaging method, global consolidation technique, etc.) to provide the lowest error rate in the system. This setting is defined as the similarity measurement technique to measure the final similarity/matching score of the two fingerprints and compare the results with other works in the next chapter.

4.4 Experimental Results

Experimental results are conducted on the dataset FCV2002_DB1. Table 4.1 shows the performance of the proposed partial fingerprint matching using LSS and LSS-R global consolidation techniques and using arithmetic, harmonic, and geometric mean (also combined with Fisher transformation) to obtain the final similarity of the two fingerprints. As mentioned in Section 4.3.2, the arithmetic mean is less affected by extreme values than the harmonic mean with the geometric mean least affected. Extreme values in terms of local similarities refers to corresponding regions that produce very high or very low similarity scores due to intra class variation and inter class similarity. The reason for extreme values obtained for both inter-class and intra-class similarities are:

- In an inter-class comparison two likely scenarios present themselves. First,

when the inter-fingerprints are dissimilar. In this case, the local similarities are low and result in a low global similarity score (desirable). Usually global consolidation or averaging techniques will not significantly affect the system's final decision on these cases. Second, when inter-fingerprints appear to be similar. The system in this case, the cause of extreme values (in a set of local similarities) is mainly due to the distorted or very similar region(s) on either the registered or query fingerprint. However, it is desirable if the global similarity is affected by low local similarities (as a result of distorted regions) and produces a lower global similarity.

- Likewise, in an intra-case comparison, typically two scenarios present themselves. First, two impressions from the same finger, where the global consolidation, averaging and correlation measures are not significantly different and can be assumed to belong to the same finger. The second is when intra-fingerprint similarity measurements vary. In this case, if one of the fingerprints is of low quality, and the other fingerprint is of very high quality (without distorted regions). Based on our observation, the frequency of intra-fingerprints that have outliers in local similarities is higher than inter-fingerprints. Therefore, not only considering the outliers do not mislead computation of global score (i.e. assigning high score to intra cases), it assists in distinguishing the inter and intra fingerprints more. That is the why the arithmetic mean is applied as an averaging method, as in most cases it results in the lowest error rate (especially when combined with Fisher transformation).

As indicated in Table 4.1, both of the global consolidation technique and averaging methods are important and affect the final result of recognition accuracy. The best result is obtained when all the local similarities are taken into account to compute the final similarity value (LSS, n = 100%). Likewise, by using lesser

Table 4.1: Comparison of the performance of the partial fingerprint matching by applying different global similarity consolidation and averaging techniques on the dataset FVC2002_DB1 in terms of the metrics EER(%).

Global Consolidation Technique	Averaging Method	$EER(\%)$
LSS, n = 100%	A.M.(Fisher)	2.6650
	A.M.	2.8150
	H.M.(Fisher)	3.0703
	H.M.	3.0714
	G.M.(Fisher)	2.8429
	G.M.	2.8531
LSS, n = 90%	A.M.(Fisher)	2.7871
	A.M.	2.8531
	H.M.(Fisher)	3.0702
	H.M.	3.0714
	G.M.(Fisher)	2.8803
	G.M.	2.8834
LSS, n = 80%	A.M.(Fisher)	2.8632
	A.M.	2.9292
	H.M.(Fisher)	3.0191
	H.M.	3.0232
	G.M.(Fisher)	2.9366
	G.M.	2.9572
LSS-R	A.M.(Fisher)	2.8334
	A.M.	2.9196
	H.M.(Fisher)	3.1519
	H.M.	3.1683
	G.M.(Fisher)	2.9689
	G.M.	2.9779

number of local similarities (LSS, n = 90% and LSS, n = 80%) the error rate increases. The lower error rate by using larger n value in LSS (as the percentage of local similarities that are considered) is mainly achieved by using all the available information provided from the local similarities.

When LSS is used as the global consolidation technique, NCC the similarity measurement and arithmetic mean (combined with Fisher transformation) the averaging method, the lowest error rate is obtained. As stated in Section 4.3.2, applying Fisher transformation on NCC values could lead to reducing the bias in averaging. The n parameter in LSS technique is set to 100% which means all

the local similarities are considered for computing the global consolidation. It should be mentioned that the lowest EER is achieved when the distribution of local similarities are transformed to normal as discussed in Section 4.3.3.

Regarding the outliers in local similarities, it is worth mentioning that by applying quality measurement techniques they are already ignored and the highly distorted regions do not participate in the final similarity score. Regarding the quality measurement, it reflects the clarity of ridges and valleys in a fingerprint region. However, the severely distorted regions were already identified and isolated; and the background and foreground were separated. Both were performed by using the mask/segmentation technique (e.g. a region of size 10×10 pixels where all the pixel values are identical). The mentioned mask technique is considered as a basic measure of fingerprint image quality which is done in many fingerprints matching methods. Thus, the severely distorted regions are isolated in order to prevent them from affecting the final similarity of the fingerprints. The quality of the sub-regions is measured for each pair of corresponding regions and they are processed in the following steps (computing their similarity) if both of them are of the minimum quality.

The two scenarios that present themselves in either an intra or an inter comparison mentioned before, and explained that avoiding the extreme values (outlier local similarities) is a promising approach. This theory is supported when regions of *very poor quality* are detected and avoided. Although using all the available information provided by a fingerprint is a reasonable approach (compared to many other methods), there are some regions that could mislead the system decision. For instance, there are some intra fingerprints that are highly distorted in some regions or are quite different from each other due to the intra-class variation. In such cases avoiding these regions not only will not lower the degree of certainty in recognition, but will also even increase it. Also transforming the data distribu-

tion to normal will help intra cases to achieve a higher mean value as discussed in Section 4.3.3.

The following sums up the discussion and contribution of this chapter:

- Partial fingerprints do not include all the structures available in a full fingerprint, hence a suitable matching technique which is independent of specific fingerprint features is required.
- Common fingerprint recognition methods are based on fingerprint minutiae which do not perform well when applied to low quality images and might not be suitable for partial fingerprint recognition.
- A region-based fingerprint recognition method in which the fingerprints are compared in a pixel-wise manner by computing their correlation coefficient is proposed. Therefore, all the attributes of the fingerprint contribute in the matching decision.
- Treating the fingerprints locally and consolidating the local similarities into one single value representing the final similarity score of two fingerprints is more appropriate than conventional methods of considering each fingerprint as one (large) single region.
- Averaging the local similarities is a good indicator of the final similarity of fingerprints as it is calculated based on all the local similarities and all local similarities contribute to the final similarity value.
- Compensating for the effect of outlier similarities is conducted by applying Fisher transformation that reduces the skew in local similarities and a less biased average.

4.5 Conclusion

In this Chapter, computing the similarity between two fingerprints is discussed. The final similarity of the two registered and query fingerprints plays an important role in fingerprint matching as the system's decision on whether two fingerprints belong to the same finger or not is based on that. In order to measure the final similarity in a way that it *better* distinguishes the intra and inter cases (considering high intra variation and inter similarity in some cases), different techniques were investigated. Global consolidation techniques were applied to ensure selecting the most appropriate local similarities according to the quality, adjacent regions and global structure of the fingerprints. Different averaging methods were investigated and applied on local similarities in order to obtain one single value (final similarity score) representing the similarity of two fingerprints. The properties of global consolidation and averaging techniques were discussed. Although the experimental results show the robustness of the proposed method with respect to the different applied techniques (no *significant* change observed by using different global consolidation, averaging and applying Fisher transformation techniques), the best result was obtained by using all the local similarities (LSS, n = 100%) and arithmetic mean (combined with Fisher transformation).

In the next chapter, according to the discussion in Chapter 3 on alignment and computing similarity/matching score in this chapter, the experimental result of the proposed partial fingerprint method is reported and compared with other works in the literature. Also, in order to measure the performance of this method in a dataset containing *only* partial fingerprints, only the partial area of the foreground fingerprint images in the dataset is considered.

Chapter 5

Performance Evaluation

5.1 Preamble

In this chapter the final partial fingerprint matching method according to the findings and discussions in previous chapters is presented. The experimental results conducted based on this method are discussed as well. As mentioned in Chapter 2, NCC is the best correlation metric to show the similarity of two fingerprints amongst other region-based metrics. Thus NCC is the metric used to align and compute the similarity degree of two fingerprints. To align the fingerprints, the proposed alignment method (Section 3.3) is used which is independent of any particular fingerprint feature. Features such as singular points, might not be found in some fingerprints which makes the proposed alignment method suitable for partial fingerprint alignment. The common regions of two fingerprints were detected based on the information provided from the alignment process as described in Section 3.6.2. In Chapter 4, different techniques to compute the similarity of two fingerprints were discussed and as shown, taking into account all local similarities and using the arithmetic mean (combined with Fisher transformation) resulted in better intra and inter comparisons according to the performance metric EER. According to the computed final similarity degree, the system makes the decision

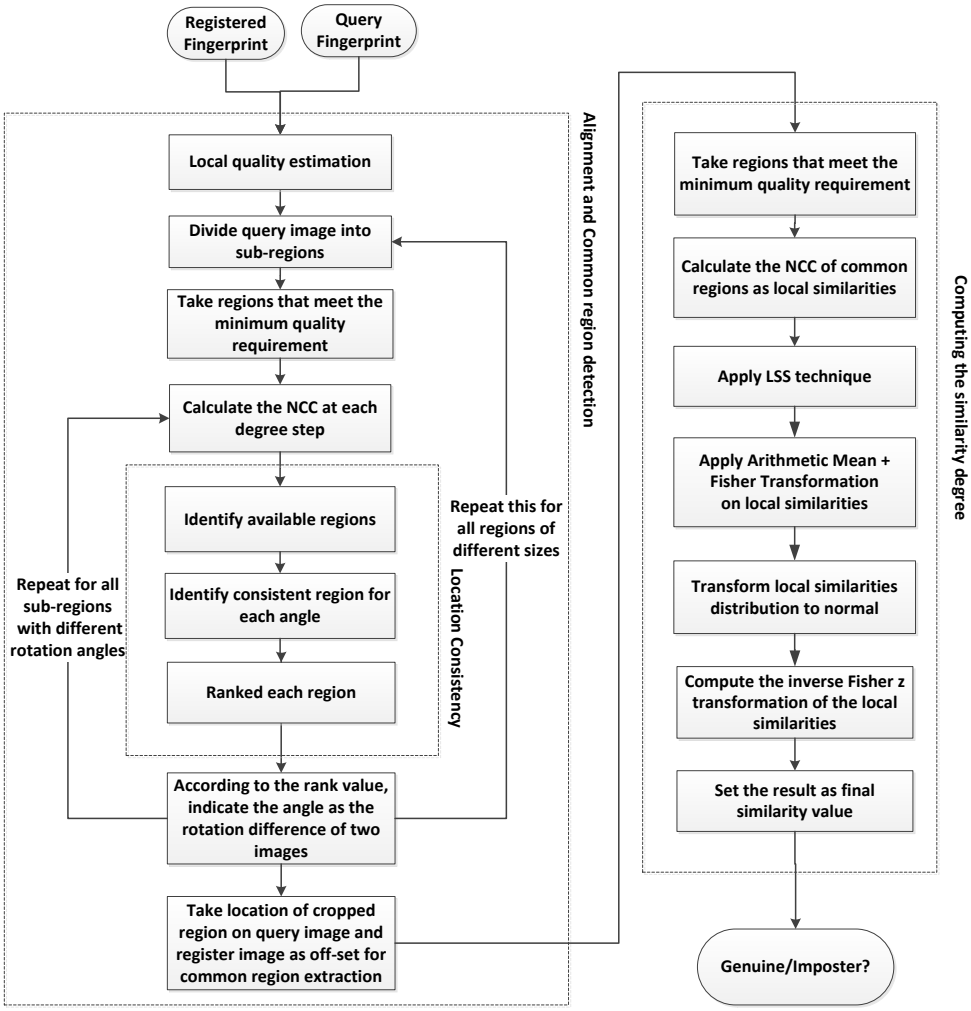


Figure 5.1: Final block diagram of the proposed partial fingerprint matching method.

whether two fingerprints belong to the same finger or not. To test the performance of the system and compare with other works, it is tested on a public dataset. To investigate the effect of partial fingerprints, a simulated partial fingerprint dataset is also generated and tested. The block diagram of the final fingerprint matching method is presented in Figure 5.1.

Table 5.1: Properties of datasets FVC_2002_DB1 and FVC_2006_DB2 used for evaluation.

Dataset	FVC2002_DB1	FVC2006_DB2
Sensor Type	Optical Sensor	Optical Sensor
Image Size	388×374	400×560
Resolution	500 dpi	569 dpi
Number of fingers	100	140
Number of impressions per finger	8	12
Total number of fingerprints	100×8	140×12

5.2 Experimental Result

The experimental result is conducted on public datasets FVC_2002_DB1 and FVC_2006_DB2 which contains 800 fingerprints from 100 different fingers (8 impressions per finger) and 1680 fingerprints from 140 different fingers (12 impressions per finger) respectively. Table 5.1 shows the description of the dataset and Figure 5.2 shows some sample fingerprints from both datasets.

The main reasons to choose the above datasets are:

- As discussed in [95], to collect the dataset FVC_2002_DB1, the participants that volunteered to provide their fingerprints, were asked to intentionally change the orientation of their finger on the scanner when scanning different impressions (to make the different impressions vary rotationally).

- No effort was made to control the image quality, the sensor plates were not systematically cleaned and high quality images were removed from the dataset.

- Due to rotation and displacement of the finger when scanning, there is often only a partial overlap between different impressions of the same finger and hence, the images in the data set include low quality and partial fingerprints as well.

- FVC_2002_DB1 dataset was obtained by using an older sensor compared to FVC_2004 and FVC_2006 datasets. Due to the older technology, the quality of the images are low in this dataset.

- For ease of comparing our result with other works. This data set is tediously used by researchers which makes comparing the results easier. Also it saves the effort of implementing others' works for comparison purposes.

As discussed in previous sections, regardless of the partiality of the fingerprints, they can be aligned, their common regions extracted, and their local and global similarities are computed. The proposed method is designed in such a way to fulfil the requirements of partial fingerprinting as well as complete/full fingerprint matching.

The experimental results are conducted on these two datasets. Level 1 matching refers to matching the fingerprint according to the information obtained during the alignment step (Chapter 3, Section 3.4). Level 2 refers to computing the similarity of fingerprints after they are aligned and their common regions are detected, as described in Chapter 4. The effect of partiality of fingerprints are also tested on this dataset by only considering different percentage of the fingerprint foreground area. The partial fingerprint test is performed on both FVC2002_DB1 and FVC2006_DB2 datasets.

Table 5.2 presents the result of matching the fingerprints in FVC2002_DB1 dataset at Level 1 as described in Chapter 3. By increasing the size of the training set, the accuracy of matching by this method improves to almost 95% as shown in Table 5.2. By using almost 5% of the dataset as the training set, the test set (remaining comparisons from the dataset, 7353 intra and inter comparisons) are recognised by 94.6% accuracy (5.6% error rate). The accuracy is computed as:

$$Accuracy = \frac{CA + CR}{TG + TI} \times 100 \tag{5.1}$$

(a) 21-4.tif

(b) 25-6.bmp

(c) 21-7.tif

(d) 25-7.bmp

(e) 21-8.tif

(f) 25-12.bmp

Figure 5.2: Sample fingerprints from FVC2002_DB1 dataset on the left and FVC2006_DB2 dataset on the right.

Table 5.2: Recognising all the fingerprints only based on alignment information (level 1 matching).

Training set size (% of the dataset):	Accuracy (%)	Error Rate(100 - Accuracy)(%)
100 + 99 ($\sim$ 2.5%)	89.8	10.2
200 + 197 ($\sim$ 5%)	94.6	5.4
300 + 249 ($\sim$ 7%)	94.5	5.5

where CA is the number of genuine comparisons that are correctly accepted, CR is the number of imposter comparisons that are correctly rejected, TG and TI are the total number of genuine (intra) and imposter (inter) comparisons respectively. The error rate is computed as:

$$Error\ Rate = \frac{FA + FR}{TG + TI} \times 100, \qquad \equiv \qquad 100 - Accuracy \tag{5.2}$$

where FA and FR refers to the number of falsely accepted and falsely rejected comparisons. According to this result, it shows that the processing done during the alignment step can provide useful information to recognise the fingerprints with about 95% accuracy. Although in this case the fingerprints are not going through the second level of matching which provides a better recognition rate (lower error rate), they are recognised more efficiently (less computational effort).

Table 5.3 shows the result of matching the fingerprints in the dataset FVC2002_DB1 and FVC2006_DB2 at Level 2 (through matching the fingerprints as described in Figure 5.1). The EER (where FAR and FRR are almost identical) is lower than the error rate achieved through level 1 (almost half). TER (where the sum of the FAR and FRR is at minimum) is also shown which is usually twice the EER. The threshold to compute EER and TER varies from dataset to dataset as it is used to point out where both FAR and FRR are identical in EER and where the sum of FAR and FRR are at the minimum value in TER. Both EER and TER metrics are explained in Section 2.8.

The low error rate achieved by processing the fingerprints at level 2 is due

Table 5.3: Recognising all the fingerprints only based on Level 2.

	FVC2002_DB1	FVC2006_DB2
FRR(%)	2.6429	2.5760
FAR(%)	2.6672	2.5535
EER(%)	2.6650	2.5648
Threshold$_{(EER)}$	0.5450	0.4665
TER(%)	4.5479	4.7111
Threshold$_{(TER)}$	0.5625	0.4870

to the proper way of defining the similarity of two fingerprints by using all the available information and processing the local similarities to consolidate them into a final matching score as discussed in Chapter 4.

Regarding the time cost of the proposed method, the matching process of two fingerprints takes about 1.5 minutes on a computer with 3.1 GHz CPU and 8 GB RAM. This time has a direct relationship with how partial a fingerprint is. The smaller the available valid regions are, the less time is required for the matching process. Considering the size of the dataset, the time cost of the proposed method, and the number of experiments conducted, the comparisons were done on Monash University High Performance Computing Cluster.

Table 5.4 [127] indicates the result of the proposed method on the FVC2002 dataset (in terms of the metric EER) where the fingerprints are decomposed to different region sizes in order to extract their common regions and compute their similarity score. In this table only pairs of fingerprints that have at least one common reference point to extract their common regions are considered as having a common reference point was the limitation in the method proposed by Zanganeh et al. in [127]. The third column in the table shows the threshold of global/final similarity score that the EER is computed on, based on the threshold value set so that both the False Reject Rate (FRR) and False Accept Rate (FAR) are identical (refer to Section 2.8 for FAR and FRR explanation). If the final similarity score of the two fingerprints is higher than this threshold, they are accepted as being from

Table 5.4: The result of the proposed method in terms of EER (%) value on dataset FVC2002_DB1 by using different region size. The last column shows the threshold used to compute the EER [127].

Proposed Correlation-Based Method	EER (%)	EER(Threshold)
Region Size = 100	3.23	0.2785
Region Size = 90	3.1	0.3041
Region Size = 80	2.73	0.326
Region Size = 70	2.44	0.3608
Region Size = 60	2.2	0.3925
Region Size = 50	2.05	0.4608
Region Size = 40	2.02	0.5241
Region Size = 30	2.03	0.5770
Region Size = 20	5.56	0.6401

the same finger (genuine user), otherwise they are rejected as being from different fingers (imposter user).

In addition, Table 5.4 indicates that the *smaller the region size* is, the *more accurate* the system performance will be. Reducing the region size, helps to lower the effect of local distorted regions since the smaller the region size is, the more precisely the distorted regions are identified. Also, the smaller the region size is, the higher the effect of low level features will be. By reducing the region size, the low level features are reflected more in comparison to a bigger region size. This is desirable especially in partial fingerprints. Also, the smaller the region size is, the more flexible it is in order to extract the maximum number of common regions in partial fingerprints.

The threshold to decide whether two fingerprints belong to the same finger or not increases when the region size decreases. The threshold is set to compute the EER in such a way to have the same FAR and FRR in the system. That leads to higher confidence in accepting/rejecting a pair of fingerprints since the higher the threshold is, the more similar two inter fingerprints have to be to get *falsely* accepted. On the other hand, the similarity of intra cases also need to be higher, but due to the mentioned points, by a smaller region size, the proposed method is

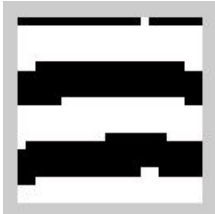


Figure 5.3: An example of a small region with the size of 20×20 pixels. The region is too small to capture the valuable fingerprint information/structure

able to reflect the similarity between two intra fingerprints reasonably.

However, due to two reasons, reducing the region size further than 30×30 pixels does not improve the accuracy. First, if the region size is too small (Figure 5.3), it does not capture enough distinguishing information of the fingerprint and the local similarities of two fingerprints will be high, regardless of inter or intra comparisons. Second, if the region size is too small, the small region cannot handle the issue of precisely locating the corresponding regions between two fingerprints due to non-linear distortion. That is why the EER is slightly increased to 2.03% after the region size is set to 30×30 pixels and further increased to 5.56% by reducing the region size to 20×20 pixels. Since very few ridges are captured in a region with the size of 20×20 pixels, the overlapped region is more likely to be found on the registered image (regardless of intra and inter comparison). That is why the EER is highly increased by setting the region size to 20×20 pixels. Therefore, the minimum region size required for any feature to be extracted is around 40×40 pixels with $\pm$ 10 pixels freedom.

Table 5.5 provides the comparison of the proposed method with previous works in terms of EER metric on the FVC2002_DB1 dataset. There is a limitation in [127] which prevent them from covering all the fingerprints in the dataset. By extracting the common regions of the two fingerprints as described in Section 3.6 at least one common reference point needs to be available. Thus, in all the comparisons a singular point existed in the fingerprint and since the area around the

reference points provides more discriminative information than any other areas, the proposed method could recognise them with 2.02% EER. However, by using Alignment method described in Section 3.3 (which only uses the fingerprint ridges) and extracting common region independent from reference point (as it might not exist in a partial fingerprint, Section 3.6.2), all the fingerprints (with no limitation) were covered with the EER of 2.665%. When the exact same fingerprints (as in [127]) are compared with the new proposed method, the EER is improved to 1.98%. The reason for an increase in EER when all the fingerprints are considered is that, when fingerprints have at least one reference point, they are likely to provide more discriminative information. Thus the reference points can play an important role in the degree of confidence in recognition. It should also be noted that a partial fingerprint may only cover a small area around the reference point, however, regions around reference points are likely to provide more information than peripheral regions [54].

The main advantage of our method compared to others is that it uses all the available dimensional attributes of the fingerprint. In addition, many methods are proposed to extract the level-3 features of the fingerprint, but extracting the level-3 features such as pores from low resolution fingerprints is very challenging. Additionally, the proposed method is able to take into account all the possible distinguishing information in the fingerprint, regardless of the image quality (not dependent on few particular features).

To demonstrate the effectiveness of the proposed region-based method, the result is compared with the single region-based correlation (conventional correlation-based method). It was observed that the averaging method improved the EER from 7.1% to 2.665% with respect to the conventional single region-based method. This improvement is achieved due to the robustness of the proposed method in handling the non-linear distortion and lowering the effect of the distorted regions in

Table 5.5: Comparison of the proposed method with previous works in terms of EER(%) value on the dataset FVC2002_DB1. The methods are roughly categorised into the three major groups of fingerprint approaches.

Category	Method	EER (%)
Minutiae-Based	Kovacs-Vajna, 2000 [134]	4.3
	Tico, 2003 [81]	4.0
	Chen, 2005 [54]	4.6
	Liu, 2005 [135]	4.3
	Gao, 2011 [82]	3.5
Non-Minutaie-Based	Sha, 2003 [136]	6.23
	Yang, 2007 [137]	3.64
	Lumini, 2006 [138]	4.2
	Qader, 2007 [91]	7.13
Hybrid	Benhammadi, 2007 [139]	4.2
	Abraham, 2011 [115]	0.75
Single Region-Based	Conventional	7.1
Proposed Region-Based Method	Omid, 2014 [127]	2.02
	The same comparisons as [127]	1.98
	whole Dataset	2.665

the fingerprints. The improvement that could be achieved through a region-based approach is also shown in Table 5.4.

Some of the methods can be roughly categorised as the minutiae-based approach. These methods typically suffer from the general limitation of minutiae-based methods which are detecting false minutiae, and not working on all the available information of a fingerprint. These issues are further highlighted when dealing with partial fingerprints (less reliability). The other group is non-minutiae-based. The features extracted in this category vary considerably, but depending on what feature is derived from the fingerprint, they may suffer from the low discriminative capability of that attribute in order to correctly recognise a fingerprint [14]. On the other hand, we conducted a pixel-wise comparison which is able to make use of level-3 features on the fingerprint which are not as sensitive as minutiae-based methods to the fingerprint quality. Although correlation-based methods are considered to be a sub-category of non-minutiae, the effectiveness and reliability

of computing the correlation of the fingerprints have been discussed previously in Chapter 2.

Cappelli et al. [79] stated that local minutiae matching techniques can be categorised into two families: *nearest neighbour-based* and *fixed radius-based*. In nearest neighbour-based family methods (i.e. Gao et al.'s approach [82]) the k closest minutiae to a central minutiae are defined as the neighbours of the central one. These methods lead to a fixed-length descriptor that can be matched efficiently. Gao et al.'s method uses the nearest neighbour structure information to match the minutiae points which carries on to global matching at the end. In addition, their method is invariant to rotation and translation which saves the effort needed to align the fingerprints. These are the main advantages of Gao et al.'s method which led to the lowest EER in the Table 5.5 (in minutiae-based category). On the other hand, further to the issues which Gao et al.'s method suffer from as a minutiae-based method, it is not able to consider the effect of non-linear distortion of fingerprint images. Also nearest neighbour-based methods are not very tolerant to missing and spurious minutiae as the objective in these methods is to find the k nearest minutiae points.

The lowest EER in non-minutiae category belongs to Yang et al.'s [83] method. Yang et al.'s method is based on extracting invariant moments of the fingerprint. Invariant moments were first introduced by Hu [84]. Hu proved that his seven moments are invariant to RTS (rotation, translation, and scaling). These moments are widely used in pattern recognition. Yang et al. applied these moments in fingerprint matching. Although their method is invariant to RTS and is efficient in terms of computation, there are some limitations in their work. The first problem is that they only make use of a small region of the fingerprints (around reference points) while the rest of the information remains unused. The second problem is that they used 75% of the dataset as training set, while all the dataset (including

the training set) is used to evaluate their method (as test set). This significantly affects the performance of the system and lead to a lower EER compared to evaluating the system only on the test set.

However, the lowest EER of all methods was achieved through using both minutiae and non-minutiae features of the fingerprint as proposed by Abraham et al. [115] by extracting the secondary features from minutiae information (as described in Section 2.7.2.1). They have used the minutiae points in addition to shape context and descriptors of the fingerprint. The EER obtained by their method is very low, though when the fingerprints are partial (Section 5.3) the accuracy is decreased.

To sum up, the proposed method which directly uses the fingerprint texture information, provides a simple but effective method to recognise fingerprints. Although using other fingerprint features can improve the accuracy of recognition even more, the EER obtained through this method is better than many other works in the literature. Also, the main focus of this research is to recognise partial fingerprints which is evaluated in the next section.

5.3 Experimental result on partial fingerprints

In order to measure the effect of the size of the partial fingerprints, a series of partial fingerprints with different sizes from FVC2002_DB1 and FVC2006_DB1 are generated. The datasets were generated by considering different sizes (as percentage) of the fingerprint foreground area at random positions as in Jea and Govindaraju [21] and Vijayaprasad [38]. The region sizes considered were 20%, 30%, 40%, 50%, 60%, 70% and 80% of the foreground area of the fingerprint. These conditions are set to simulate where a partial fingerprint is provided. To test the FRR, there are $(8 \times 7)/2 \times 100 = 2800$ and $(12 \times 11)/2 \times 140 = 9240$ genuine tests and $(100 \times 99)/2 = 4950$ and $(140 \times 139)/2 = 9730$ imposter com-

Table 5.6: Comparison of the performance of the partial fingerprint matching with different sizes at random position on dataset FVC_2002_DB1 in terms of TER.

(%)	TER (%)			
Image size	Vijayaprasad [38]	Jea [21]	Abraham [115]	Proposed Method
80	2.70	2.89	5.1885	4.5623
70	3.25	3.41	6.2247	5.3861
60	4.95	5.03	5.7338	5.8326
50	5.77	5.98	9.5288	6.3375
40	10.4	10.36	10.7772	8.3880
30	-	17.73	16.1747	10.7316
20	-	29.24	25.8213	17.7947

Table 5.7: Comparison of the performance of the partial fingerprint matching with different sizes at random position on dataset FVC2002_DB1 in terms of EER.

(%)	EER (%)		
Image size	Jea [21]	Abraham [115]	Proposed Method
80	1.74	3.2643	2.8546
70	1.77	3.5076	3.2150
60	2.52	3.4203	3.7653
50	3.17	5.4147	4.5014
40	5.25	5.8945	5.7217
30	9.12	8.3258	7.2311
20	17.11	14.6893	12.4027

parisons to test the FAR in FVC2002_DB1 and FVC2006_DB2 respectively. The experimental results for FVC2002_DB1 dataset is shown in Table 5.6 in terms of the metric TER, Table 5.7 in terms of the metric EER, and Table 5.8 which indicates the number of cases that each method was able to process (as sensitivity analysis). The performance of the proposed method in terms of EER and number of cases processed by each method for the dataset FVC2006_DB2 are also shown in Table 5.9 and Table 5.10 respectively.

As the results show, if only 50% of the fingerprint foreground area is considered, our methods performs better than Abraham et al.'s method which produces the lowest EER for the FVC2002_DB1 dataset. Also, the proposed method performs better than all the other methods when only 40% of the fingerprint foreground area is considered in terms of the metric TER. Since there might be a small finger-

Table 5.8: Sensitivity analysis of the partial fingerprint matching methods w.r.t. the image size in terms of the percentage of the cases that each method was able to proceed when only partial size of the fingerprint foreground area was considered.

(%)	Percentage of the cases processed. $Total_{(Intra,Inter)}$	
Image size	Abraham [115]	Proposed Method
80	$7749_{(2799,4950)} \simeq 100\%$	$7746_{(2797,4949)} \simeq 100\%$
70	$7750_{(2800,4950)} \simeq 100\%$	$7746_{(2798,4948)} \simeq 100\%$
60	$5254_{(1432,3822)} \simeq 68\%$	$7732_{(2784,4948)} \simeq 100\%$
50	$4145_{(1068,3077)} \simeq 53\%$	$7692_{(2745,4947)} \simeq 99\%$
40	$3181_{(784,2397)} \simeq 41\%$	$7666_{(2717,4949)} \simeq 99\%$
30	$1105_{(245,860)} \simeq 14\%$	$7382_{(2478,4904)} \simeq 95\%$
20	$314_{(61,253)} \simeq 4\%$	$4255_{(1405,2850)} \simeq 55\%$

print area left after considering only a portion of the foreground area (the original fingerprint might a partial), some fingerprints provide limited information to be used by the matching method. Therefore, the number of cases that could be recognised is less than the total number of comparisons in the dataset. The number of cases that could proceed in the proposed method and Abraham et al.'s method are shown in Table 5.8. These numbers are not available for the Jea and Govindaraju's [21] and Vijayaprasad's [38] methods. The EER and TER of the proposed method is lower than Abraham et al.'s method in almost all the cases when part of the of the fingerprint area was considered, also the number of cases that were processed by the proposed method is higher or the same as theirs.

For the dataset FVC2006_DB2 when only a partial size of both registered and query fingerprints' foreground was considered, the result of the proposed method is compared with Abraham et al.'s method. The source code of their method is available at MathWork.com [140]. Same as for FVC2002_DB1 the EER and the number of cases processed by our method is superior to theirs. As represented in Table 5.9, the EER of Abraham et al.'s method is very high for this dataset when fingerprints are of partial size. The reasons for the high error rate of their method is that the parameters are tuned for the FVC2002_DB1 dataset without changing the parameters for a different dataset their method produces a very high

Table 5.9: Comparison of the performance of the partial fingerprint matching with different sizes at random positions on dataset FVC2006_DB1 in terms of EER.

(%)	EER (%)	
Image size	Abraham [115]	Proposed Method
100	11.0921	2.56
80	41.0636	3.3150
60	37.3257	3.6271
40	31.5654	4.3497
20	21.63	5.1945

Table 5.10: Sensitivity analysis of the partial fingerprint matching methods w.r.t. of the image size in terms of the percentage of the cases that each method was able to processed when only a partial size of the fingerprint foreground area was considered. (FVC2006_DB2)

(%)	Percentage of the cases processed. $Total_{(Intra,Inter)}$	
Image size	Abraham [115]	Proposed Method
80	$18970_{(9240,9730)} \simeq 100\%$	$18884_{(9224,9660)} \simeq 100\%$
60	$18970_{(9240,9730)} \simeq 100\%$	$18885_{(9220,9665)} \simeq 100\%$
40	$18634_{(9078,9556)} \simeq 98\%$	$18578(9155, 9423) \simeq 98\%$
20	$12023_{(5817,6216)} \simeq 63\%$	$11103_{(6155,4948)} \simeq 58\%$

error rate.

In addition, as the sensitivity analysis shows (Table 5.10), the number of cases processed in both methods is higher than the dataset FVC2002_DB1. This is due to the higher resolution and image size in FVC2006_DB1 dataset. Also, both methods can cover almost 98% of the comparisons in this dataset due to the large fingerprint size and high resolution when 40% or more of the foreground area is considered.

To sum up, as the experimental result shows, the proposed partial fingerprint recognition method performs better than other related works in the literature, in particular when fingerprints are partial. This is due to the independence of the proposed method to the fingerprint size, available region, and any particular feature such as minutiae and reference points.

5.4 Conclusion

In this Chapter, the experimental results of the proposed partial fingerprint matching method were discussed. Based on the investigation in Chapter 2, Normalized Cross Correlation is the best correlation metric to indicate the similarity of two fingerprints. Therefore, NCC was used to measure the similarity between two fingerprints (locally). The fingerprints were aligned as described in Chapter 3 using the fingerprint ridge structure. The final similarity of two fingerprints was computed in Chapter 4 by applying the global consolidation technique and lowering the bias in averaging the local similarities by applying Fisher transformation. Then the experimental result was conducted on FVC datasets and compared with other methods in this Chapter. Considering the miniaturization of fingerprint scanners and as *partial* fingerprints bring more challenge to recognition process, the result was also tested on partial fingerprint datasets by considering partial size of the fingerprint foreground area. As result shows, the proposed method performs better in most of the cases when compared with other methods. It fulfils the main objective of this research as to propose an appropriate method for partial fingerprint matching. The next chapter is the conclusion of the whole thesis and possible future work.

Chapter 6

Conclusion

In this thesis extensive research has been conducted to investigate various techniques in fingerprint recognition and to improve the accuracy of the partial fingerprint recognition system. The main focus of this research has been on partial fingerprint alignment and similarity/matching score measurement. The experimental result are provided to evaluate the proposed alignment and similarity measurement techniques and to compare the results with other works. The results show that the proposed partial fingerprint matching method is superior to all of the recent related methods. In the following sections, the summary of the thesis and research contributions is presented.

6.1 Thesis Summary and Research Contributions

Biometric recognition is a useful and reliable tool to verify a person's identity compared to the traditional password or token based systems as it cannot be forgotten or stolen. Fingerprinting is one of the lowest cost and yet accurate biometric traits for recognition and has attracted a lot of attention in recent years. Due to the high intra-class variation and inter-class similarity, achieving a foolproof system has not been feasible yet. Miniaturization of the fingerprint scanner, presence of

a small overlap between the fingerprints, highly distorted regions in some areas of the fingerprint, lack of all the available features in the partial fingerprint compared to a full fingerprint, uncertainty about which part of the finger is provided and etc. all provide obstacles in partial fingerprint recognition compared to full fingerprint recognition.

In Chapter 2, the literature review of the fingerprint matching is presented. According to the literature, using fingerprint texture is a promising approach to be used along with or as an alternative to minutiae information especially for *partial* fingerprint matching. Many researchers emphasized on the need for investigating other fingerprint features besides minutiae points. A region-based approach is an effective tool that can measure the similarity of fingerprints reliably. This is due to the ability of the region-based measurement to detect and utilize all of the fingerprint features in their similarity score. Directly using the fingerprint ridge structure and treating the fingerprints as images can be done by computing the correlation of the fingerprints. A comparison of eight correlation metrics presented and discussed lead to the conclusion that Normalized Cross Correlation (NCC) is the metric that best overcomes shortcomings. Therefore, when it was needed to compare two fingerprints (sub-regions of fingerprints), the NCC of the fingerprint regions was measured.

Alignment as an important step in a region-based approach was discussed in Chapter 3 by presenting the proposed partial fingerprint alignment method. Since in a region-based matching approach, pixels of the two images are compared, even a small rotational difference of the images (corresponding regions) might result in an inaccurate matching/similarity score. In order to address this variation of fingerprints, and to ensure the same regions in the two fingerprint are compared, they need to be aligned. Also, as in partial fingerprint matching, only a small region (of a full fingerprint) might be available, the alignment need to be done

independent from partial fingerprint size, regions, and any particular feature such as reference points. The proposed method is able to rotationally align the fingerprints by only using the fingerprint texture information which is always available in a partial fingerprint regardless of its size.

Traditionally, the similarity of fingerprints was compared globally by considering each fingerprint as one big region. However, treating the fingerprints locally improves intra fingerprints variation, by providing the ability to detect and isolate or reduce the effect of distorted regions. In order to perform a local matching of fingerprint sub-regions, the corresponding regions needed to be identified. As in alignment, this step also had to be performed by only using the information that is provided in a partial fingerprint. Also, since the fingerprints are two dimensional images (that are rotationally aligned now), locating one common point can be used to identify the corresponding region in both fingerprints. Since the reference points are considered as reliable features, (if present in the partial fingerprint) they were used as a common offset point to locate the corresponding sub-regions of the two fingerprint. If no common reference point was available in both images, the locations of the two sub-regions that matched with the highest rank/score in alignment were used as the common offset point in both images for the purpose of locating the corresponding regions.

In addition to the effect of similarity measure, how the fingerprint local similarities are consolidated into a single value (global/final similarity) also plays an important role. In order to measure the similarity score of two fingerprints, the similarity is measured in two steps. The similarity is computed locally, as local similarities, by measuring the NCC of each corresponding regions. How to combine the local similarities into a single value, representing the final similarity score of two fingerprints is also important. The final similarity is computed in such a way that it reduces the effect of distorted regions, takes into account all the information

provided by local similarities, reduces the skew in local similarities which result in biased averaging and transforms the local similarity distribution to a normal distribution. All these helped to assign a higher similarity score to intra cases and compensate for the intra class variation resulting in better distinguishing the intra and inter cases according to the metric EER.

To measure the effectiveness of the proposed method and compare the result with other works, the proposed method was tested on public datasets as the benchmark. Although the error rate of the proposed method is lower than many other related works, the lowest error rate (compared to other methods) was achieved when the fingerprints were partial as the main focus of this research was on partial fingerprint matching.

This research confirms the use of rich information provided by fingerprint texture information for recognition purposes especially in partial fingerprint. However, using other features such as minutiae could also lead to improve the efficiency and accuracy of this method. As stated by the researchers, there is a need to use features other than minutiae as an alternative or along side with them. Using the minutiae features (especially in good quality fingerprints) can be used to recognise good quality images and if the fingerprints are of low quality or partial use their texture information.

6.2 Future Work

The future work of this research can be summarised as follows:

- The proposed alignment method can tackle the difficulties in partial fingerprint alignment. However, using other strategies to increase the efficiency of this process without losing accuracy must be considered in the future. This goal can be achieved by investigating fingerprint features, in conjunc-

tion with or separately from each other, as well as applying different features and methods according to the fingerprint properties. The method to align the fingerprints can be different according to the fingerprint size, quality and availability of the features. This will lead to faster alignment at least in cases where less computation is required.

- Using fingerprint statistical analysis to prioritise the region/features that present more unique to the fingerprint or are more robust in with-standing distortion compared to other regions/features is also promising to improve the matching accuracy.

- Designing a fingerprint template protection technique is an important phase in any fingerprint recognition system. It refers to protecting/securing the fingerprint templates stored in the system dataset to prevent compromise of the templates.

- In combing local similarities into a single value representing the final similarity score of two fingerprints, an adaptive setting according to the two fingerprints being matched is promising. The settings for the global consolidation techniques mentioned in this research is fixed for the whole dataset regardless of the characteristics of fingerprint. Considering the quality of the regions which the local similarities were obtained from should be considered in global consolidation techniques.

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