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Quantifying the impact of missing minutiae on latent fingerprint identification

A thesis presented by

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Declaration of Authorship

I, Emilio Francisco Ferreira Mehnert, declare that this thesis titled, Quantifying the impact of missing minutiae on latent fingerprint identification and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
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Emilio Francisco Ferreira Mehnert
Monterrey, Nuevo León, November, 2020

Dedication

To my parents, who have provided unconditional support throughout my life. Thank you both for teaching me the meaning of hard work.

To my girlfriend, Sofía. Thank you for saving time with me.

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Quantifying the impact of missing minutiae on latent fingerprint identification
by
Emilio Francisco Ferreira Mehnert

Abstract

Fingerprints are the patterns left behind by the ridges of the skin on the tips of the fingers and are commonly used as an identifying characteristic of individuals. Fingerprints are identified by comparing specific features between them. Minutiae are the most commonly used features for fingerprint identification.

In an attempt to simulate and study human error when manually marking minutiae, we performed a study to determine the performance of a fingerprint matcher when it is input a subset of the apparently available minutiae in a latent fingerprint. This situation is analogous to an expert overlooking existing minutiae or misleadingly annotating a minutia when there is none. This was done by removing minutiae that were manually marked by latent fingerprint experts, and comparing matching score and rank-n identification performance to the original expertly-marked fingerprint.

We found that randomly removing minutiae from latent fingerprints generally causes the recognition rate to go down in a closed set comparison experiment. We removed all possible combinations of one, two, and three minutiae from latent fingerprints and found that when removing minutiae it is more likely for the matching score to go down instead of up. We also found that in some cases, removing even one minutia can cause a fingerprint not to be identified. And that if removing a set of minutiae from a fingerprint caused a drop in matching score, it was more likely that it would cause a drop in rank-n identification performance rather than an increase.

Finally, we created a dataset based on the minutiae removed and their change in scores to train and evaluate several machine learning models to predict how a minutia will affect the matching score of a fingerprint if it is marked. Our best model was able to predict with a better-than-random chance if a minutia will increase or decrease the matching score of the fingerprint with a .601 AUC.

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Chapter 1

Introduction

Fingerprints are the patterns left behind by the ridges of the skin on the tips of the fingers. Sir Francis Galton, a pioneer in the field of fingerprint identification, calculated that the probability of two individuals having the same fingerprints is 1 in 64 billion [12], and no reports exist of two identical fingerprints [20]. Therefore, these patterns are considered to be unique from one individual to another. This has allowed fingerprints to be used as an identifying characteristic of individuals, a practice that has been in use since the late nineteenth century [40]. Fingerprint matching has forensic, civilian, and commercial applications [20].

Fingerprints are identified by comparing specific features between them, they can be the fingerprints themselves, their minutiae, or other features [23]. Maltoni *et al.* [23] have classified such features in three levels, as can be seen in Figure 1.1.

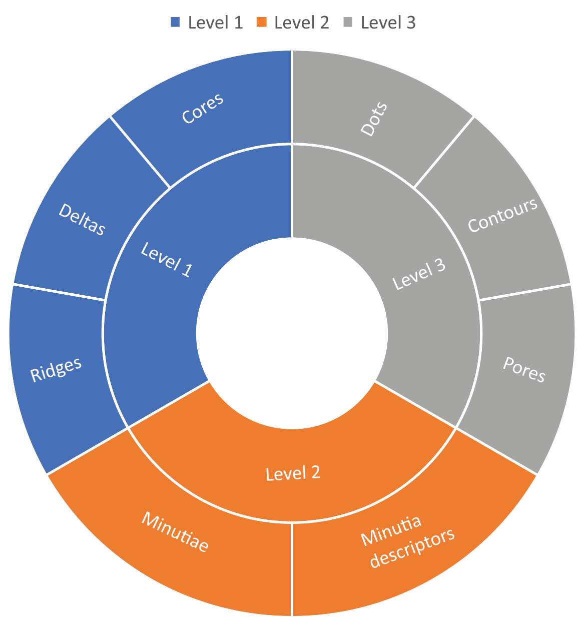

Figure 1.1: Fingerprint Features by level.

Level 2 features, called minutiae are the most commonly used features for latent fingerprint identification [39]. Galton is widely considered the first person to categorize minutiae and observe that they remain unchanged throughout an individual's lifetime [12]. Minutiae are points where the fingerprint ridges become discontinuous. Although there are other types of minutiae, the most commonly used minutiae for identification are when the ridge comes to an end (line ending) and when the ridge splits in two (bifurcation) [40]. Figure 1.2 shows examples of fingerprints and minutiae.

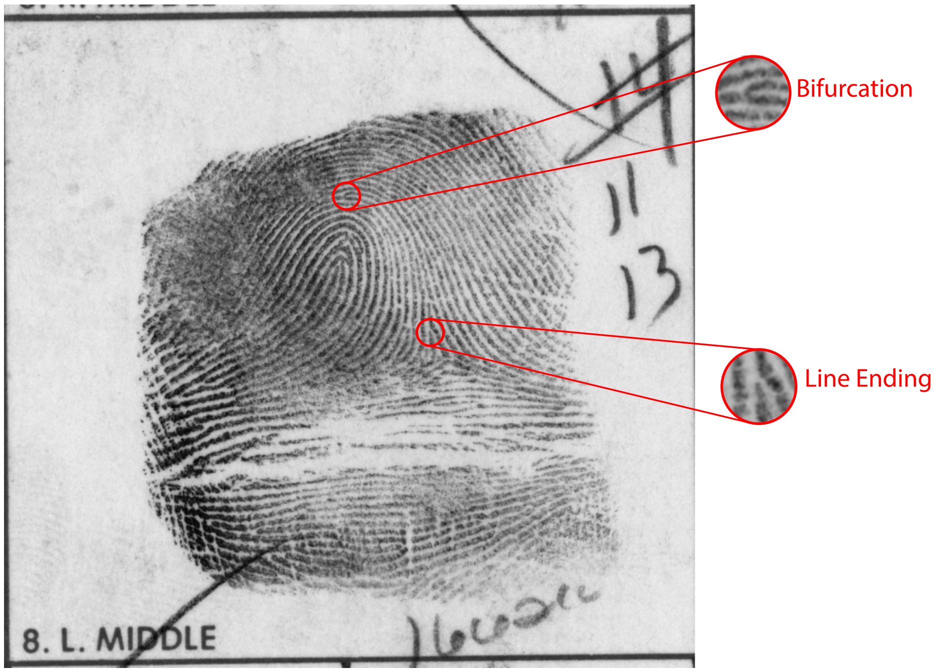

Figure 1.2: Example of a fingerprint and minutiae. Original Image from NIST SD27 Database.

Fingerprint impressions can be deliberately stored by ink or by electronic means. On the contrary, latent fingerprints are left behind when a person manipulates an object. Chemicals present in the tips of the fingers, such as sweat or oil, are responsible for latent fingerprints [23]. These latent fingerprints can be retrieved using a variety of techniques using chemical methods [20, 23] and other physical and instrumental techniques [20].

Latent fingerprints are important in the context of forensic identification. They are used to identify suspects and victims of crimes [23] and are often provided as evidence at trials. Due to the sensitivity of these applications, an accurate method of identifying fingerprints is desired.

The importance of minutiae detection is better understood when you consider that identification of latent fingerprints has obtained the best results when minutiae-based identification algorithms are used [1].

Current automatic minutiae extraction algorithms on latent fingerprints do not achieve human-level performance [32]. Latent fingerprint minutiae extraction is still a task performed partially by human latent fingerprint examiners [1, 20], and thus, can be prone to errors. Additionally, different latent fingerprint examiners may mark different minutiae on the same latent fingerprint [37].

In an attempt to simulate and study human error, this thesis quantifies and discusses the effects of missing minutiae on latent fingerprints when input into a latent fingerprint matching algorithm.

To the best of our knowledge, there has been no study to determine the performance of a fingerprint matcher when it is input a proper subset of the available minutiae in a latent fingerprint. This situation occurs when an expert overlooks existing minutiae or misleadingly annotates a minutia when there is none.

By studying how human error can affect the performance of latent fingerprint matching algorithms, we aim to show the importance of developing methods for assisting latent examiners in marking latent fingerprint minutiae.

Understanding how to better match latent fingerprints to impressions is an area of active study [29, 38]. We know minutiae extraction algorithms and latent fingerprint matcher performance both depend on the quality of the input fingerprint images [23] and latent fingerprint matchers have better performance on higher-quality latent fingerprint images [4, 38]. Table 1.1 shows the average minutiae in latent fingerprints divided by quality in the NIST Special Database 27. This means that the greater number of minutiae, the better the performance of the matching algorithms.

Quality	Average minutiae count
Good	32
Bad	18
Ugly	12

Table 1.1: Average minutiae count in latent fingerprints divided by quality in NIST SD27.

However, the effects that specific minutiae have on the performance of latent fingerprint matching algorithms have not been studied and could be beneficial in developing better minutiae extraction algorithms as well as better matching algorithms. By attempting to quantify the effects that missing minutiae have on latent fingerprint matchers, we begin to understand how specific minutiae affect the performance of matching algorithms.

1.1 Problem Description

Latent fingerprint minutiae extraction is a task still performed by human latent examiners, but there has been little research into understanding how human errors affect latent fingerprint identification performance.

The table 1.2 shows recent automatic minutiae extraction methods and their performances. There is currently no method that achieves human-level performance. Due to this, we believe an approach that attempts to help human examiners perform their work more efficiently and correctly rather than replacing them is desirable. To design such an approach, it is needed to understand how human examiners make mistakes and what the effects of these mistakes would be. This thesis attempts to analyze the effects of these mistakes.

For us to be able to understand the effects of mistakes, we need to develop a method that artificially makes such mistakes.

Authors	Method	Year	Testing Data	Performance
Nguyen *et al.* [26]	Convolutional Neural Network with inception-resnet.	2018	NIST SD27	.71 F1 Score.
Sankaran *et al.* [31]	Stacked Denoising Sparse AutoEncoders.	2014	NIST SD27	46.8 Patch Prediction Accuracy.
Tang *et al.* [33]	Fully Convolutional Network with pre-trained models.	2018	NIST SD27	.53 F1 score.
Tang *et al.* [34]	Unified network with domain knowledge.	2018	NIST SD27	.63 F1 Score.

Table 1.2: Recent automatic minutiae extraction methods for latent fingerprints.

1.1.1 Types of Mistakes

There are two types of mistakes that can be made when marking minutiae. These types are false positives or what are called spurious minutiae, and false negatives which are also referred to as missing minutiae. Spurious minutiae occur when a minutia is marked where there is none, and missing minutiae occur when a real minutia is not marked.

Since the performance of minutiae extraction algorithms is dependant on the quality of the input fingerprint images [23], both of these mistakes are common in programs and algorithms designed to extract minutiae from latent fingerprints due to the low-quality nature of these fingerprints.

1.1.2 Simulating the Human Error

Previous studies show that latent examiners do often disagree with each other when marking minutiae on latent fingerprints [37]. When these disagreements happen, at least one of the examiners is making a mistake. Without an understanding of how humans make mistakes, we are not able to reproduce them accurately. However, we can simulate many possible mistakes based on certain assumptions, and evaluate their effects.

Missing minutiae can be simulated by removing ground truth minutiae. However, we consider spurious minutiae harder to simulate because simulated spurious minutiae would have to be similar enough to real minutiae that a human examiner would believe they are real minutiae.

1.1.3 Understanding the effect of mistakes

Once the occurrence of a mistake is simulated, we need to evaluate the effect that the mistake has on the performance of identification. We need to decide what metrics to use and how we can use the information gained from the evaluation performance relative to the specific type of mistake.

We can measure the effects of mistakes in two ways:

- By measuring the change in the matcher score of a specific latent fingerprint matching algorithm when comparing the latent fingerprint with the impression.
- By measuring the change in the rank-n identification of that specific fingerprint.

Once we measure the effects of these mistakes, we can characterize the minutiae that are responsible for those mistakes and determine if there are a set of features of a specific minutia that accurately predict the effect of the mistake on the matcher score or the rank-n identification of a fingerprint.

1.2 Hypothesis and Research Questions

After reviewing the problem, we propose the following hypothesis: If a single or multiple minutiae are removed from the input of a latent fingerprint matching algorithm, matching performance will be affected negatively in a noticeable manner. Furthermore, we can predict how much the matcher score of a matching algorithm will be affected when removing a specific minutia depending on features of that minutia.

Which leads to the following research questions:

- How much does the latent fingerprint matching score vary when it is input a proper subset of the set of minutiae from a latent fingerprint?
- Does a change in matching score translate into a change of matching performance?
- Can we predict how matching score will be affected when a specific minutia is removed?

1.3 Objectives

The general objective of this thesis is to quantify the effects of missing minutiae from latent fingerprints on latent fingerprint matching algorithms.

The specific objectives of this thesis are as follows:

- Measure the difference in matching score when a matching algorithm is input a proper subset of the minutiae of a latent fingerprint compared to when a matching algorithm is input all of the minutiae in the latent fingerprint.
- Determine if fingerprints that have a lower matching score when a matcher is input a proper subset of the minutiae in the latent fingerprint consistently have a lower rank in a closed set comparison experiment by generating proper subsets of minutiae and counting the instances when this happens.
- Determine if fingerprints with a higher matching score when a matcher is input a proper subset of the minutiae in the latent fingerprint consistently have a higher rank in a closed set comparison experiment by generating proper subsets of minutiae and counting the instances when this happens.

- Determine if it is possible to predict the change in matching score when a minutia is removed by using machine learning algorithms on a dataset based on minutiae features and measuring their area under the Receiving Operating Characteristic (ROC) curve.

1.4 Contributions

The contributions of this thesis are the following:

- The first algorithm that simulates human mistakes in the latent fingerprint minutiae marking phase.
- The first empirical study that quantifies, in terms of a cumulative match characteristic curve and matching score, the effects of missing minutiae in latent fingerprint identification.
- A novel method of determining how a fingerprint's matcher score will be affected by marking a minutia in real-time.

1.5 Thesis Structure

The rest of this document is organized as follows: chapter 2 contains the theoretical framework to support our research as well as previous research closely related to our own. Chapter 3 presents our study, which includes the experimental framework and the results of our experiments. Finally, chapter 4 contains our conclusions and possible future works.

Chapter 2

Related Work

2.1 Theoretical Framework

This section presents the theoretical framework to support this research. It begins with the relevant necessary information about fingerprints and their use as a biometric identifier. Then it moves on to explain the relevancy of latent fingerprints. We then explain latent fingerprint identification and the relevance of minutiae in this context. Next, we talk about automatic minutiae detection. Furthermore, we show some previous works in the performance of human latent fingerprint examiners.

2.1.1 Fingerprints as an Identifying Characteristic

To talk about fingerprints, we must first explain their relevance and validity as a biometric identifier. Fingerprints are the patterns left behind by the ridges of the skin on the tips of fingers. As early as 1892, Sir Francis Galton observed that these patterns remain unchanged throughout the lifespan of a person [12]. These patterns are also considered unique [12], and there are no reports of two individuals having the same fingerprints [20]. Due to these characteristics, fingerprints have been used as an identifier for forensic, criminal, and access control purposes [20].

To identify a fingerprint, specific points of interest within the print are used. These are called features. There are different types of features. However, the authors of the Handbook of Fingerprint Recognition [23] have classified these features in three levels. Figure 1.1 summarizes these different features and their classifications, but below we provide a more extensive explanation:

1. Level 1 features: Also called *singular points*. These points are where fingerprint ridges delineate specific patterns [23]. These patterns can be classified into three different categories: loops, deltas, and whorls. These features are good enough for classification and indexing but are not good enough for fingerprint matching [23].

2. Level 2 features: These are ridge-specific characteristics. One hundred fifty different total ridge characteristics have been identified [23], but most of them are rarely observed in fingerprints or depend on the quality of the fingerprint impression. The two most prominent level 2 features are line endings and bifurcations. Line endings are points

where the continuity of the ridge stops or breaks. Bifurcations are points where a ridge splits to form two different ridges. These two kinds of points are called **minutiae**. Even in different impression conditions, minutiae are usually stable [23].

3. Level 3 features: These features are considered fine details because they are detected at the intra-ridge level. These features include ridge width, shape, curvature, and dots. Although these features are mostly invariant, they require high-resolution fingerprint images to be extracted [23].

The combination of these features is what makes a fingerprint unique [12]. Identifying these features on two different prints and comparing them allows a claim to be made that two fingerprint impressions came from the same finger, and thus, from the same person [12]. This is why identifying these features is a task of importance.

Fingerprints can be acquired in many ways. However, most of them fall into one of three categories: they can either be deliberately captured using ink and paper, they can be captured and stored digitally using an electronic fingerprint scanner, or they can be obtained as latent fingerprints, which are prints unintentionally left behind by humans when manipulating objects, and consist of sweat or other chemicals often present on the tips of fingers [23].

There are two significant fields of study related to fingerprints. The first one is fingerprint verification, which consists of matching two specific fingerprints and determining if they originated from the same finger [20]. The second important field is latent fingerprint identification, which consists of matching one latent fingerprint to a fingerprint impression coming from the same finger, in order to identify a subject [20]. The corresponding impression is searched in a collection of fingerprints (e.g., a database) [20].

Minutiae

Minutiae are level 2 features present in fingerprints. Although there are many types of minutiae, the two most commonly used for identification are bifurcations and line endings.

Line endings are point on the fingerprint where the continuity of the ridge abruptly ends. Bifurcations are points in the fingerprint where the ridge splits into two different paths. Figure 1.2 in chapter 1 shows both of these types of minutiae.

To work with minutiae, one must have a representation of such features. Given a fingerprint image, a minutia can be represented by the following data [23]:

1. The position of the minutia on the X-axis.

2. The position of the minutia on the Y-axis.

3. The orientation of the minutia.

4. Type of minutia (e.g., line ending, bifurcation, etc.)

The orientation of the minutia is represented as an angle θ from the horizontal axis to the tangent of the ridgeline at the minutia point [23].

While some algorithms and systems benefit from or require the type of minutia, others do not. Therefore, a single minutia point in a fingerprint can be represented as a tuple (x, y, θ).

2.1.2 Latent Fingerprints

This section explains the context of latent fingerprints, necessary to understand the relevance of the proposed research and the challenges it presents.

Latent fingerprints are fingerprints left behind by chemicals often present at the tips of the fingers [20]. These chemicals may be sweat, sebum, or grease [20, 23], which are not usually visible to the naked eye. To obtain these fingerprints, forensic experts may need to use different techniques to reveal and store them, including chemicals [20, 23] and other physical and instrumental techniques [20]. Once revealed, the prints are often photographed or scanned. Due to the nature of this process and the surfaces on which the prints are found, the latent fingerprints retrieved are prone to presenting distortion and background noise.

Latent fingerprints are mostly used to identify suspects of crimes [20]. This makes latent fingerprint identification a crucial area of interest for research due to its applications in law enforcement. Furthermore, errors in latent fingerprint identification can have severe consequences because failing to identify a latent fingerprint may cause a criminal to go unidentified, or a false identification can lead to an innocent person being accused of a crime they did not commit [15]. An example of the latter situation is the case of the wrongful implication of Oregon lawyer Brandon Mayfield in the 2004 Madrid bombings due to a false positive match of a latent fingerprint found at the crime scene with one of Brandon Mayfield's fingerprints on the FBI database [28]. This is why high accuracy in latent fingerprint identification is desired.

Latent Fingerprint Identification

Latent fingerprint identification is one of the most studied topics in biometrics in the last 50 years [16]. Systems that perform latent fingerprint identification are called AFIS (Automatic Fingerprint Identification Systems). These systems became popular due to the need for law enforcement agencies to automate the fingerprint identification process [23]. AFISs perform several steps of the fingerprint identification process. However, these systems are far from perfect. They often need human intervention in the minutiae extraction step due to the unsatisfactory performance of automatic minutiae extraction algorithms [1, 20].

Matching fingerprints is considered a challenging problem due to the large number of possible variations between two impressions of the same finger (intra-class variations). Factors responsible for intra-class variation include displacement, rotation, variable pressure, and skin condition, among others. Two fingerprints from the same finger may look very different. [23]

There are three primary automatic fingerprint matching approaches [23]:

1. *Correlation-based matching:* Fingerprints are superimposed, and the correlation between images is calculated for different alignments.

2. *Minutiae-based matching:* Minutiae are extracted from both fingerprints and compared. These approaches can also use minutiae descriptors, which include other features and information around extracted minutiae.

3. *Non-minutiae feature-based matching:* Compare fingerprints in terms of features extracted from the ridge pattern.

Most fingerprint identification systems and algorithms use minutiae-based matching [23, 26]. Furthermore, the most commonly used feature representation for fingerprints is minutiae descriptors [39]. Additionally, minutiae-based matching is accepted as a proof of identity on most courts of law around the world [23].

Latent fingerprint matching is an area of active study [4, 29, 38], but even recent research suggests that the performance of these matching algorithms is not perfect, especially when dealing with large background databases [38].

2.1.3 Automatic Minutiae Detection

AFISs typically have automatic feature extractors, but they often require manual intervention by latent fingerprint experts to manually mark minutiae [1, 20]. Therefore a method that performs at least as good as a latent fingerprint examiner is desired.

Minutiae extraction techniques can be divided into two: Minutiae extraction on greyscale fingerprint images and minutiae extraction on binarized fingerprint images [23, 20].

Extraction on Binarized Fingerprint Images

Binarization involves converting greyscale images to binary images (black or white pixels), and most binarization approaches use ridge-thinning, which is transforming ridges to lines of 1-pixel thickness [23] (see Figure 2.1). This approach has four main problems [23]:

1. Information is lost during the binarization process.
2. Binarization and thinning are time-consuming.
3. Thinning often introduces spurious minutiae.
4. Low-quality images do not provide satisfactory results.

(a) Original greyscale fingerprint. (b) Binarized fingerprint. (c) Binarized and ridge-thinned fingerprint.

Figure 2.1: Comparison of original greyscale fingerprint, binarized fingerprint, and ridge-thinned binarized fingerprint. Images taken from [23].

Extraction on Greyscale Fingerprint Images

Minutiae extraction techniques on greyscale fingerprint images use the original latent fingerprint image as input [23]. These techniques aim to overcome the problems that binarization-based extraction techniques have. These approaches work better than binarization and ridge thinning related methods but underperform on noisy fingerprint images [23, 34]. Figure 2.2 shows an image of a greyscale fingerprint on which minutiae extraction would be performed.

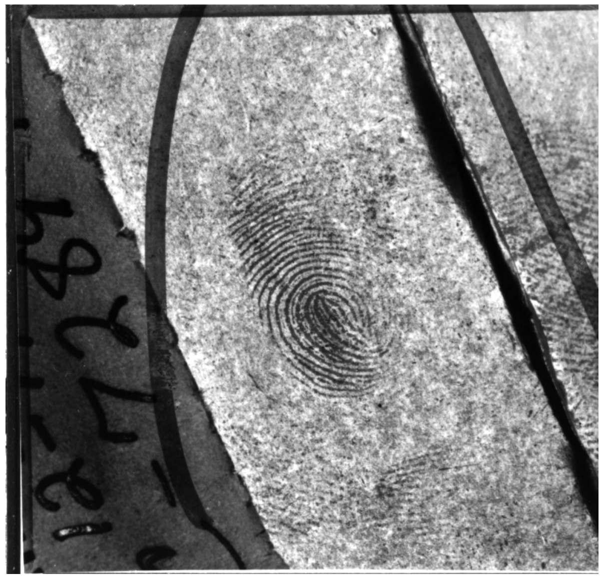

Figure 2.2: Image of a greyscale latent fingerprint. Image is from the NIST SD27.

Maio *et al.* [22] proposed a method of finding minutiae on greyscale images by following the ridgeline of the latent fingerprint. This algorithm views the ridgeline as a set of continuous points that are local maxima in one direction. This algorithm obtains an approximation of the ridgeline pattern, which allows it to find minutiae. Several authors proposed variations on this method, such as Jiang *et al.* [17], Liu *et al.* [18], and Chang *et al.* [7].

Nilsson *et al.* [27] proposed a method of minutiae extraction on greyscale images using Linear Symmetry properties.

Fronthaler *et al.* [11] proposed using both Linear Symmetry properties and Parabolic Symmetry properties to detect minutiae in greyscale images.

However, the most promising and recent methods of extracting minutiae from greyscale images of latent fingerprints involve the use of Deep Learning. Table 1.2 in chapter 1 lists some of these methods and their performances.

These methods outperform previous methods on latent fingerprint images. For example, Nguyen *et al.* [26] proposed MinutiaeNet, which is a convolutional neural network composed of two different sub-networks. The first network estimates the position and location of the minutiae in the latent fingerprint image, and the second network refines the results provided by the first network. This approach reaches an F1 score of .71 on the NIST SD27.

Another example of Deep Learning being used to extract minutiae directly from latent fingerprint images comes from Tang *et al.* [34]. FingerNet is a convolutional neural network that integrates typical steps of the manual latent fingerprint minutiae extraction process, such as image enhancement and fingerprint segmentation. They integrate these steps into convolutional layers with fixed weights, and later they add additional convolutional layers. Afterward, the fixed weights are released for the network to learn. FingerNet is reported to have a .63 F1 score on the NIST SD27.

2.1.4 Latent Fingerprint Matching Algorithms

This section presents the theoretical framework regarding latent fingerprint matching algorithms. We also briefly explain two latent fingerprint matching algorithms that we use for our experiments.

Matching fingerprints is considered a difficult problem, mainly because two fingerprints originating from the same finger have large variability [23]. Human latent examiners consider several factors when matching two fingerprints. Some of these factors include global pattern configuration, the minimum number of minutiae, and concordance of minutiae between two fingerprints [23]. Automatic fingerprint matchers do not necessarily function in the same way as human latent examiners, but the automatic matching algorithms are inspired by the human latent examiner process [23].

Fingerprint matching algorithms compare two fingerprints and return a similarity score or a decision if whether two fingerprints came from the same finger or not [23]. When two fingerprints are considered to have come from the same finger, they are called **mated** prints, and when they are not considered to have come from the same finger, they are called **non-mated** [23].

Fingerprint matching algorithms operate mostly on intermediate representations of fingerprints, such as minutiae sets or minutiae descriptors [23].

The representation of a fingerprint an algorithm tries to match to any other is called the **input**. The representation of any fingerprint being compared to the input is called a **template** [23].

This thesis uses two different minutiae-based matching algorithms to test our hypotheses and answer our research questions. We chose minutiae-based matching because it is the most widely used fingerprint matching method [23, 26].

Minutia Cylinder-Code

The first matching algorithm we use to perform our experiments is called Minutia Cylinder-Code (MCC) by Cappelli *et al.* [6]. This algorithm defines a representation of a fingerprint-based on three-dimensional structures, each associated with a given minutia.

The three-dimensional representation of each minutia is constructed using basic minutia features such as its angle and the distances between itself and other minutiae. Figure 2.3 shows a visualization of the three-dimensional structure associated with each minutia in the MCC algorithm.

The MCC algorithm computes a local similarity score for each minutia and then consolidates these similarity scores to output a global similarity score between two minutiae sets.

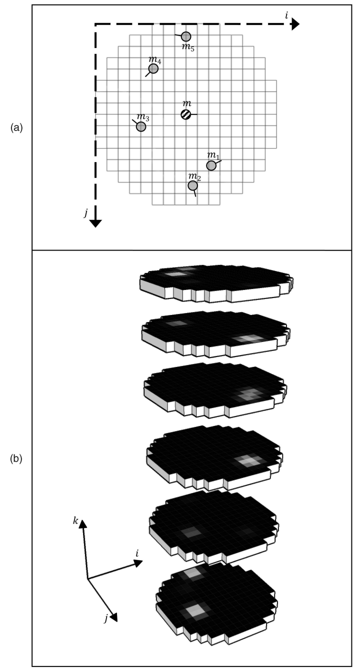

Figure 2.3: An example visualization of the three-dimensional structure associated with each minutia in the Minutia Cylinder-Code algorithm. Image taken from [6].

Deformable Minutiae Clustering using Cylinder Codes

This fingerprint matching algorithm is called Deformable Minutiae Clustering (DMC) by Medina-Pérez *et al.* [24].

This matching algorithm is independent of minutiae descriptors. This means it can use any minutiae descriptor. The experiments conducted in this thesis using DMC use Cylinder Code [6] minutiae descriptors to perform local matching.

This algorithm is based on the use of clustering to improve robustness to non-linear transformations in often present in latent fingerprint matching. This algorithm also computes a global similarity score for both sets of input minutiae sets.

2.2 Previous Works

This section presents some previous works that are closely related to the work done in this thesis. This includes both works done related to human performance in latent fingerprint minutiae extraction and matching, as well as works related to the performance of fingerprint matching algorithms when the input is modified or distorted.

2.2.1 Research on the performance of humans when matching latent fingerprints

In this sub-section, we present works that study the performance of human latent fingerprint examiners when marking or matching latent fingerprints. These works are intended to show that even experts can make mistakes and serve as the motivation for our research on the effects of mistakes in this area.

Accuracy and Reliability of Forensic Latent Fingerprint Decisions

Ulery *et al.* [35] tested 169 latent print examiners to determine the accuracy and reliability of their decisions regarding latent fingerprint identification.

The study created a total of 744 of latent and exemplar fingerprints. From those fingerprints, 520 were mated pairs of fingerprints, which means both the template and latent fingerprints in the pair came from the same finger, and 224 were nonmated pairs, meaning the template and latent fingerprints did not come from the same finger. Each pair was reviewed on average by 22 different examiners.

Each latent fingerprint examiner was presented with 100 random fingerprint pairs out of the total pool of 744. Participants used custom software developed for the study, which allowed for limited capabilities of image processing. Examiners were given weeks to analyze all fingerprint pairs.

This study considers four outcomes in each comparison. These four outcomes are consistent with the ACE-V methodology:

- No value.
- Exclusion (the prints do not come from the same finger).
- Inconclusive.
- Individualization (the prints do come from the same finger).

In this study, false positives are considered only when a VID decision was reached in a nonmated pair. Similarly, false negatives are only considered when a VEO decision was reached in a mated pair.

The results of this study showed that 5 examiners committed 6 false positive errors which result in an overall false positive rate of 0.1%. Results also showed that at least 85% of examiners committed a false negative error, but the overall false negative rate is 7.5%.

Fortunately, no false positive errors were repeated on the same fingerprint by two different latent examiners, which leads the authors to believe that blind verification would solve false positives. The authors also believe that blind verification would solve most of the false negative errors.

This study presents an initial approach to studying the performance of human latent examiners, but it does so without analyzing the performance of the examiners in the individual steps of the latent fingerprint identification process. However, the results are relevant to our work because it is one example that shows that even human experts make mistakes in this area.

Repeatability and Reproducibility of Decisions by Latent Fingerprint Examiners

Ulery *et al.* [36] tested a group of latent fingerprint examiners to determine if they reached consistent decisions when comparing latent fingerprints to impressions.

In this study, the researchers tested 72 latent fingerprint examiners twice, several months apart, on the decisions they made regarding 25 template and latent fingerprint pairs on whether they are mated or nonmated pairs.

The repeatability data from the first test came from a previous study [35], which we mention in this thesis in section 2.2.1, by the same authors. In the first test 169 latent examiners participated, but in the retest, only 72 latent examiners participated. The retest was conducted seven months later than the first test.

The latent and template fingerprint pairs used for the second test are the same 744 used in the first test. Each of the 72 examiners was assigned 25 pairs on the retest with the following criteria:

- 9 nonmated image pairs. If an examiner had committed a false positive error on a nonmated image pair, they were assigned that pair again. The rest of the pairs were assigned at random from the pool.
- 16 mated image pairs partitioned in the following manner:
  - 11 mated image pairs on which the examiner had not committed a false negative error, selected at random from the pool.
  - If the examiner had committed false negative errors, these mated prints would be selected, but only up to 5.
  - If there were any remaining pairs to be selected, these would be, once again, from the pool. These remaining pairs would not be used in the study as not to skew the results from examiners who had committed false negative errors.

The reproducibility data is only from the first test, but this article incorporates the results.

The authors found that examiners repeated 89.1% of their individualization decisions. Examiners also repeated 90.1% of their exclusion decisions. Changed decisions most often resulted in an inconclusive assessment. Furthermore, no false positive errors were repeated. Results also show that in cases on which examiners were not consistent with themselves there was also disagreement between them.

This study builds upon the work done previous study [35] by the same authors, and presents more precise information on how human experts perform while performing latent fingerprint identification. Unfortunately, it still does not analyze the individual steps that are taken by examiners while performing latent fingerprint identification. Nevertheless, the study still shows that human latent fingerprint examiners do make mistakes, and serves as additional motivation for our research.

Interexaminer Variation of Minutia Markup on Latent Fingerprints

Ulery *et al.* [37] performed a study to quantify the differences in minutiae markup from one latent fingerprint examiner to another.

In this study, researchers tested 170 volunteer latent fingerprint examiners. Each examiner marked the minutiae in 22 different latent and exemplar fingerprint pairs following the ACE-V protocol. The total pool of latent-exemplar pairs was 320.

Each pair of corresponding latent and exemplar prints was marked, on average, by 12 examiners. It is important to note that examiners mark the exemplar fingerprint as well as the latent fingerprint. Examiners did not mark minutiae type or direction. The examiners also marked a local clarity map by painting the fingerprint with six different colors indicating six different levels of clarity. The authors simplified the clarity levels into two: clear areas and unclear areas.

To determine the reproducibility of a single minutia, and to account for small differences in the exact location of a minutia, the authors used a clustering algorithm. It is important to note that minutiae type and direction are not accounted for in clustering different minutiae markups from different examiners because examiners did not record that information. An example of the clustered minutiae marked on a fingerprint, as well as the clarity of the fingerprint, can be seen in figure 2.4.

They found that the median reproducibility of minutiae markup was 82% in clear areas and 46% in unclear areas. According to the authors, some factors contributing to the low reproducibility are:

- Differences in training and expertise from one latent fingerprint examiner to another.
- Ambiguity of the continuity of unclear regions of the latent fingerprint *i.e.*, regions on which examiners were not sure if minutiae should be marked or not have minutiae with low reproducibility.

The authors determined that examiners' clarity markup is a strong indicator of the reproducibility of the minutiae they marked, and that areas on which the latent fingerprint is not clear, examiners disagree on the markup of the minutiae.

This study is very useful to our research because it clearly shows that human expert examiners often disagree on which points of interest in a latent fingerprint are minutiae and which are not. This allows us to conclude that human latent examiners make mistakes on the minutiae markup step of the latent fingerprint examination process. However, the authors do not analyze the impact of the variation on minutiae markup on latent fingerprint identification algorithms, which we aim to do in this thesis.

2.2.2 Research on the Performance of Matching Algorithms With Distorted Fingerprints

In this section, we present research which is closely related to our research. Here, we present one study that performs a similar analysis to our own. We highlight the key similarities and differences of this study to ours.

White-Box Evaluation of Fingerprint Matchers

Grosz *et al.* [13] perform a white-box evaluation of three fingerprint matchers in terms of how different perturbations in fingerprints affect the matching score of said matchers.

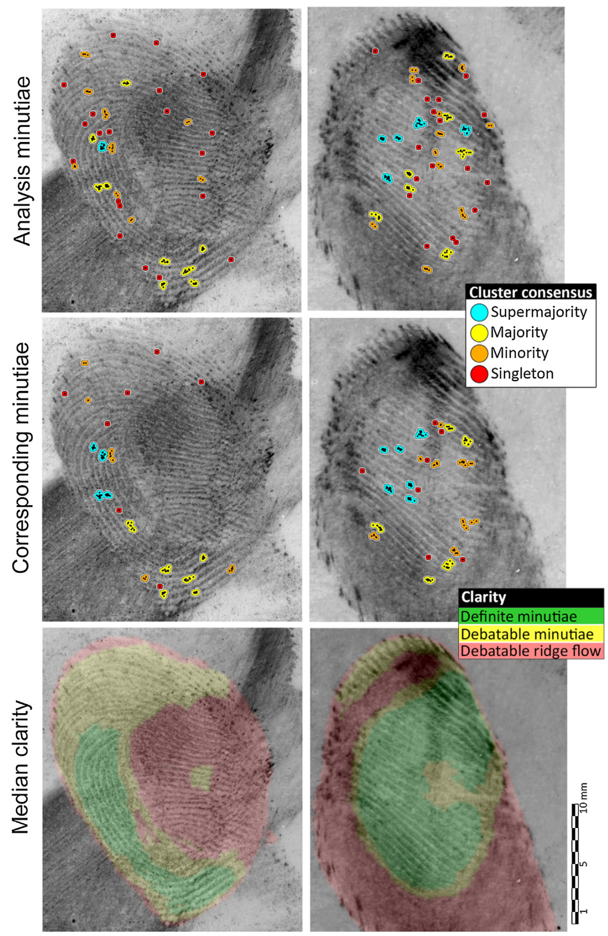

Figure 2.4: An example of a latent fingerprint that was marked by several latent examiners on its minutiae and clarity. This image shows three rows: The first row shows a latent-exemplar fingerprint pair and the minutiae marked on the analysis phase with the corresponding clusters for each minutia. Row 2 shows the same exemplar pair, but only with the corresponding minutiae marked. Row 3 shows a median clarity map as marked by several latent examiners. Image taken from [37].

In this study, the authors evaluate three different fingerprint matchers. They use two unnamed commercial-off-the-shelf (COTS) minutiae-based matchers and one open-source matcher called SourceAFIS.

The authors evaluate the robustness of these matchers against controlled perturbations of the fingerprints, specifically, perturbations of the minutiae sets.

The fingerprint dataset they used to test the robustness of the matcher is a synthetically generated fingerprint impression dataset using SFinGe [5]. They generated 5,000 different "master" fingerprints and generated two different impressions from each. This also generated one ground truth minutiae set for each fingerprint.

The authors ran experiments with several different types of perturbations. The perturbations they considered were:

- Moving and rotating minutiae.
- Adding spurious minutiae and removing ground truth minutiae.
- A non-linear distortion of the minutiae sets.
- Combining moving and rotating minutiae with the addition of spurious minutiae and removal of ground truth minutiae.

The first two perturbations were generated by using a multivariate Gaussian Distribution model, which had parameters the researchers considered to model real possible perturbations. The non-linear perturbations were generated by using a non-linear distortion model learned from distorted fingerprints. An example of some of the perturbations can be seen in figures 2.5 and 2.6.

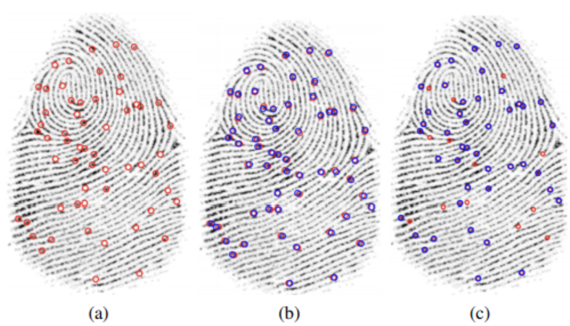

Figure 2.5: An example of the perturbations done by Grosz *et al.* in [13]: (a) is the original minutiae, (b) is randomly moving each minutia, and (c) is adding and removing minutiae. Image taken from [13].

Using these distortions, the authors performed two different experiments:

- An uncertainty analysis resulting from realistic amounts of perturbation and distortion.
- An evaluation of the recognition performance of each minutia-based matcher on increasing levels of perturbation and distortion.

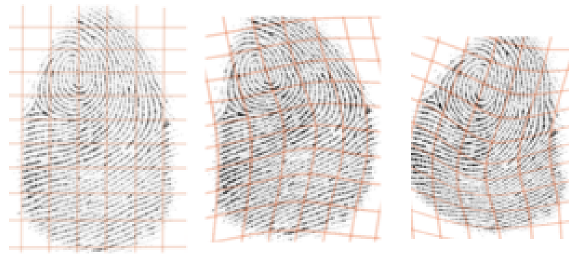

Figure 2.6: Examples of non-linear distortions applied to fingerprints as was done by Grosz *et al.* in [13]. Images taken from [13].

To perform the uncertainty analysis, they generated 100 perturbations per perturbation type, per generated fingerprint. Similarity scores are obtained and used to calculate a global uncertainty score relating to each perturbation type.

When performing the second experiment, the authors increased the perturbation parameters over the course of eight iterations. The results of this experiment are reported as true acceptance rate at a fixed false acceptance rate of 0.01%. They also calculated impostor scores for each perturbation type, on each iteration.

The authors found that the non-linear distortion is the perturbation that reduced the mean of the similarity scores the greatest, followed by the combined perturbation, and after that, the removal of ground truth minutiae.

Similarities and Differences To Our Work

This work is similar to our own in the manner that we both test the performance of fingerprint matching algorithms when altering the ground truth minutiae set of fingerprints. However, there are several key differences in our work which makes it unique:

- Whereas they use synthetically generated fingerprint impressions, we use real latent fingerprints in our research.
- They perform several types of perturbations including the removal of ground truth minutiae, we only perform the removal of ground truth minutiae.
- Their work only randomly removes minutiae according to a multivariate Gaussian Distribution, but we systematically remove minutiae to determine the effect specific minutiae have on the performance of latent fingerprint matchers.
- They report their results by performing an uncertainty analysis associated with each perturbation type, whereas we take into account matching score, rank-n identification rates, and CMC curves.

In conclusion, we believe that, while this work can be considered similar to ours, we perform different experiments, with different data, and with a different focus.

2.3 Conclusions

Latent fingerprint identification is a critical task in law enforcement which is still performed by human experts. Several steps of the latent fingerprint identification process are considered hard because automatic methods have not yet been able to reach the performance level of humans. One example of this is marking minutiae in latent fingerprints. Minutiae are critical to latent fingerprint identification since they are the features most used to compare two fingerprints to one another.

Since marking minutiae in latent fingerprints is a task still performed by human examiners, it is prone to mistakes due to human error. Some authors have studied how different human latent fingerprint examiners mark minutiae on the same fingerprints and have concluded that there is often variation in which landmarks of a fingerprint are considered minutiae between examiners.

There is a study on how distortions affect the performance of fingerprint matchers, which could be considered similar to our own work. We compare and contrast this work and conclude that our work is substantially different.

Chapter 3

Experimental Framework and Results

This chapter presents the study we have done to quantify the effects of missing minutiae in latent fingerprint matching algorithms. It includes details about the data used to perform the study, the methods used to perform the study, details about the experiments themselves, and the results of the experiments.

We have performed three experiments attempting to simulate human error, specifically, missing minutiae. In these experiments, we remove ground truth minutiae from latent fingerprints in several ways and determine how the evaluation of latent fingerprint matchers change.

Additionally, we have used the information we gathered from these experiments to create several datasets with the intention of using these datasets to develop a classifier that would allow us to determine the impact of a specific minutia on a matching algorithm.

It is worth noting that ground truth minutiae were not removed from fingerprints in cases where a fingerprint was to be left with less than six minutiae, based on what INTERPOL uses as a minimum minutiae count for their AFIS [14].

3.1 Experimental Framework

In this section, we present the experimental framework of four experiments, including the datasets we used and which measures we use to evaluate the results of each experiment.

3.1.1 Data sets

For our experiments, we used a latent fingerprint database from the National Institution of Standards and Technology (NIST). The used database is the so-called NIST Special Database 27 (NIST SD27). This database consists of 258 latent fingerprints with their matching rolled tenprints. Each fingerprint has minutiae extracted and validated by a team of professional latent examiners. This dataset was partitioned by the examiners based on the quality of the latent fingerprints. The fingerprints were categorized into the qualities of good, bad and ugly, where good is the best quality and ugly is the worst.

Additionally, for some experiments, we used the NIST SD4 as a background database. This database contains images of two thousand rolled fingerprints. Minutiae for this database were extracted using Verifinger.

3.1.2 Randomly removing a set of minutiae

The first experiment consisted of removing a specific amount of minutiae from each fingerprint, decided at random, and determining how the CMC curve of the dataset was affected. This experiment had two variants:

- In the first variant, we removed a fixed number of minutiae from each of the fingerprints in the dataset.
- In the second variant, we removed a fraction of the minutiae from each of the fingerprints in the dataset.

For the first variant, we removed from 1 minutia up to 20 minutiae. For the second mode, we removed from 0.05 of the minutiae in each fingerprint up to 0.75 of the minutiae, in 0.05 increments. When removing a proportion of the minutiae in a fingerprint, we round down. For example, if a fingerprint has 17 minutiae and we are removing 0.1 of the minutiae, we only remove 1 minutia. Each experiment was run ten different times, with different, randomly removed minutiae. The results of the ten experiments were then averaged for a final result.

For each amount of minutiae removed, we run the experiment ten times with different randomly removed minutiae. The results are then averaged.

This is a closed set identification experiment, meaning that the latent fingerprint matchers try to find a corresponding impression for each latent fingerprint, and that the corresponding impression is guaranteed to be in the background database. We evaluate the experiment using a Cumulative Match Characteristic (CMC) curve. CMC curves are used for several one-to-many comparisons in which those comparisons are ranked based on a score, which, in this case, is the matching score. If a fingerprint is found within the first n matches, we consider that this fingerprint is found in rank n identification.

3.1.3 Removing all possible combinations of one, two, and three minutiae

For further testing, we decided to remove all possible combinations of one, two, and three minutiae from each latent fingerprint in the NIST SD27 and then obtain the matching score of the modified fingerprint and the corresponding impression for each of the two different latent fingerprint matching algorithms we use. We then compare the matching score of the original fingerprint to the matching score of each version of the fingerprint.

This allows us to assign a score to each minutia, pair of minutiae, or triplet of minutiae. This score reflects the matching score of a specific algorithm when that minutia or set of minutiae is removed from the fingerprint. It allows us to determine which minutiae affect the matching score of a latent fingerprint matching algorithm the most.

For each amount of removed minutiae (one, two, and three), we only consider fingerprints which, when removing that amount of minutiae, would not have less than 6 minutiae left.

In total, we created over a million different versions of the fingerprints in the NIST SD27. Table 3.1 shows a break down of the number of fingerprint versions created.

With this information we can determine how matching score behaves when removing minutiae. Additionally, it allowed us do two more experiments. The first one involves finding

Amount removed	Number of combinations
1 minutia	5,241
2 minutiae	74,173
3 minutiae	935,478
Total	1,014,892

Table 3.1: Total amount of possible combinations of minutiae sets when removing one, two, and three minutiae from each latent fingerprint of the NIST SD27.

the most influential minutiae in a fingerprint in matching score, and it is detailed in section 3.1.4.

The second experiment involves the creation of a dataset based on the information obtained and the creation of several machine learning models with this dataset. This is detailed in section 3.1.5.

3.1.4 Evaluating the three best and three worst combinations of minutiae

Since the previous experiment allows us to determine the effect that each minutia or set of minutiae has on the matching score of a specific latent fingerprint matching algorithm, we use this information to determine the top three and the bottom three sets of one, two, and three of minutiae for each fingerprint. We then remove the top and bottom three sets of minutiae and determine how the rank-n identification of the fingerprints in the NIST SD27 changes.

The top three sets are the sets which have the largest positive change (or smallest negative change) in matching score compared to the score obtained by ground truth minutiae set. Similarly, the bottom three sets are the sets with the largest negative change (or smallest positive change) in matching score when compared to the score obtained by the ground truth minutiae set. This can mean that the top three can have negative values, and the bottom three can have positive values in some edge cases.

To determine the top three and the bottom three sets of minutiae, we use algorithm 1, which includes the steps taken in the previous experiment. This algorithm only considers one fingerprint and one set amount (one, two, or three).

Figure 3.1 shows a visualization of the most influential minutiae from a latent fingerprint in the NIST SD27 when evaluated with the DMC matcher.

Once the top three and bottom three minutiae sets have been obtained from each fingerprint for experiments removing one, two, and three minutiae, we use this information to perform new closed set comparison experiments. In these experiments, we use the matching score of each version of the fingerprint we obtained in experiment two to determine how the change in score reflected in the rank-n identification of each fingerprint.

3.1.5 Creation of Dataset and Classification of Minutiae

In the second experiment, we determined the impact each possible combination of one, two, and three minutiae have on matching score for two different latent fingerprint matchers. With

Algorithm 1: Algorithm to obtain the top and bottom three minutiae sets from a fingerprint in terms of change in ranking score.

Data: Each possible minutiae set S_i where $0 < i < k$. Ground truth minutiae set S_o.
Result: The top three and bottom three sets of minutiae.
Start;
obtain ground truth set matching score to matching tenprint fingerprint σ_o;
for *each minutiae set S_i in the fingerprint* **do**
  remove S_i from the ground truth set S_o to get Sc_i ;
  obtain matching score σ_i of remaining ground truth minutiae set Sc_i;
  calculate change in score by subtracting σ_i from σ_o resulting in Δ_i;
end
order all $\Delta_i, 0 < i < k$ ascending;
obtain the first three Δ_i and the last three Δ_i of the ordered list;
obtain the corresponding S_i to the previously obtained Δ_i and return all the (S_i, Δ_i) pairs;
End;

this information, we created a dataset to determine if it is possible to predict if removing a minutia will have a positive or negative effect of matching score.

This dataset was constructed by using the results of removing every possible combination of one minutia from a fingerprint, as described in section 3.1.3 for the DMC matcher. We created features based on the location of each minutia and the distances of neighboring minutiae. We designed two different kinds of features: The first type of feature counts the amount of minutiae in a radius neighboring the specified minutia. The second type of feature is the distance from the specified minutia to the n closest minutia. We define a class value, which we attempt to predict. Finally, the class values *positive* and *negative* were used for minutiae that, after being removed, increased or decreased the matching score, respectively.

In the end, each data point in the created dataset has the following information:

- d[0-5]: Each of these features has the distance from the minutia to the closest minutia (d[0]), to the second closest minutia (d[1]), and so on.
- r[15, 30, 45, 60, 75, 90]: Each of these features counts how many minutiae there are in a radius (of 15 pixels, 30 pixels, and so on) around the specified minutia.
- class: Either a positive or negative impact on the matching score.

In total, this dataset has 12 features and one class feature. It contains 5,215 instances, of which 1,991 are positive examples (minutiae which increase the matching score when removed), and 3,224 are negative examples (minutiae which lower the matching score when removed).

We tested eight different supervised classifiers. We selected popular classifiers of different types to get varied results. For each algorithm, we did five-fold distribution balanced stratified cross-validation [25], which is used for imbalanced class problems. We evaluated

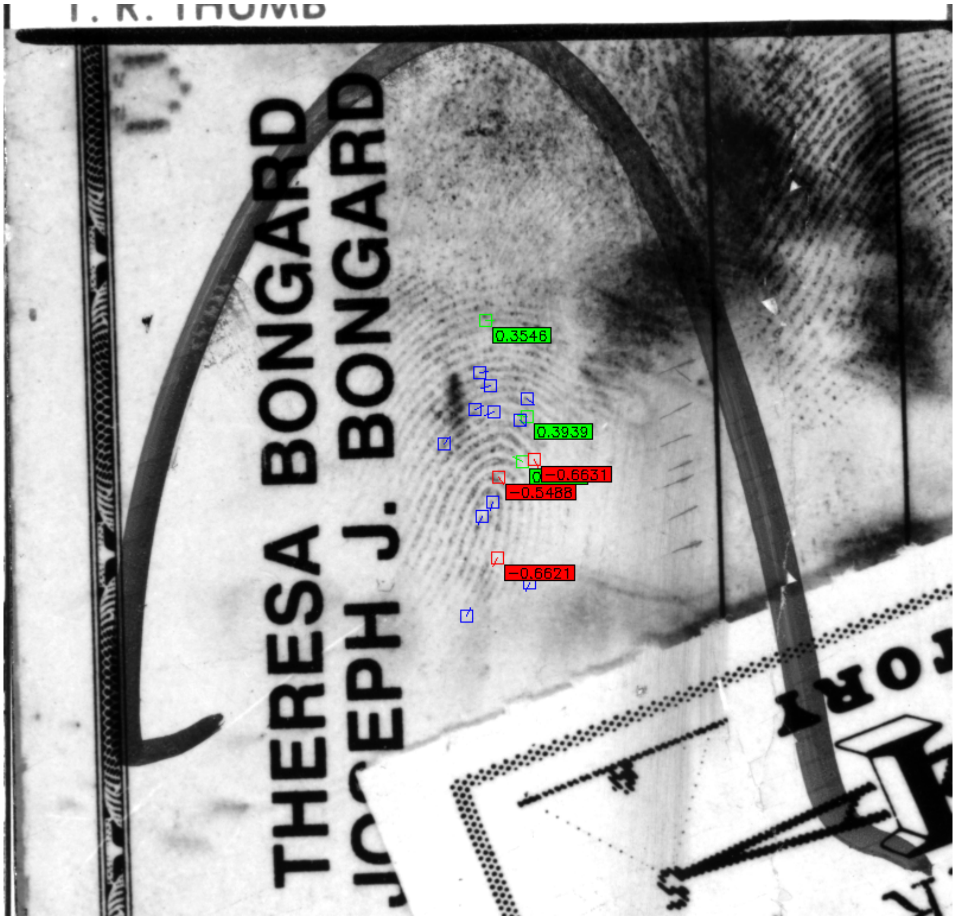

Figure 3.1: A fingerprint from the NIST SD27 with a visualization the most influential minutiae sets. This example considers the set size as 1. Minutiae are marked by a square with a line denoting the orientation. Red squares are the minutiae that have the largest negative impact (or smallest positive impact). Green squares are the minutiae that have the largest positive impact (or smallest negative impact). The rest of the minutiae are marked with blue squares.

each algorithm with the area under the receiver operating characteristic curve (AUC) [9]. The AUC is calculated as:

$$\frac{1 + \mathrm{TPR} - \mathrm{FPR}}{2} \tag{3.1}$$

where TPR is true positive rate and FPR is false positive rate.

The eight supervised classifiers that we used were:

- Fisher's Linear Discriminant (FLDA) [10].
- Quadratic Discriminant Analysis (QDA) [10].
- PBC4cip [21].
- Random Forest [3].
- Bagging [2].

- Logistic Regression [19].
- Multilayer Perceptron [30].
- Support Vector Machines (SVM) [8].

3.2 Results and Discussion

This section presents the results obtained from each of the experiments and discussion about such results.

3.2.1 Randomly removing minutiae results

In this subsection, we present the results from the experiment in which we randomly remove a set amount of minutiae from latent fingerprints, detailed section 3.1.2. These results consist of CMC curves for the different datasets and modes of the experiment.

When removing a specific amount of minutiae, the rank 100 CMC curve of the NIST SD27 with a background database of NIST SD27 + NIST SD4 was worse the more minutiae were removed from the fingerprints. This was the case for both the DMC matcher and the MCC matcher, although the DMC matcher CMC curve tended to decrease less than the MCC matcher curve.

Figure 3.2 shows a comparison between the CMC curves when removing different amounts of minutiae from each fingerprint in the dataset when using the DMC matcher. Figure 3.3 shows a similar comparison but with the MCC matcher.

When a specific number of minutiae are removed from each fingerprint in the dataset, the drop in identification rate performance appears to be linear. Figure 3.4 shows a plot of number of minutiae removed against identification rate across several rank-n identification points for the DMC matcher. Figure 3.5 shows a similar plot, but using the MCC matcher.

When removing a proportion of the minutiae in every latent fingerprint, the CMC curve was lower the larger a proportion of minutiae was removed. Figure 3.6 shows a comparison between the CMC curves when different proportions of minutiae are removed using the DMC matcher. The plot shows different CMC curves for each proportion of minutiae removed from 0.1 of the minutiae in each fingerprint, up to 0.75 of the minutiae in each fingerprint. Figure 3.7 shows a similar comparison but using the MCC matcher.

When removing a proportion of minutiae when using the MCC matcher, the CMC curves for removing 0.1 and 0.2 of minutiae cross each other. This can be seen in figure 3.7. We believe that when removing a very small amount of minutiae from a fingerprint, there are some edge cases in which it can improve identification performance.

We can see that, generally, removing minutiae from fingerprints has a negative impact on latent fingerprint identification performance when using latent fingerprint matchers. We can see that identification performance decreases in a linear fashion when removing a specific amount of minutiae from each fingerprint in the dataset. Another observation is that when removing minutiae, the decrease in identification performance is more drastic when performing rank-n identification for lower values of n than it is for higher values of n.

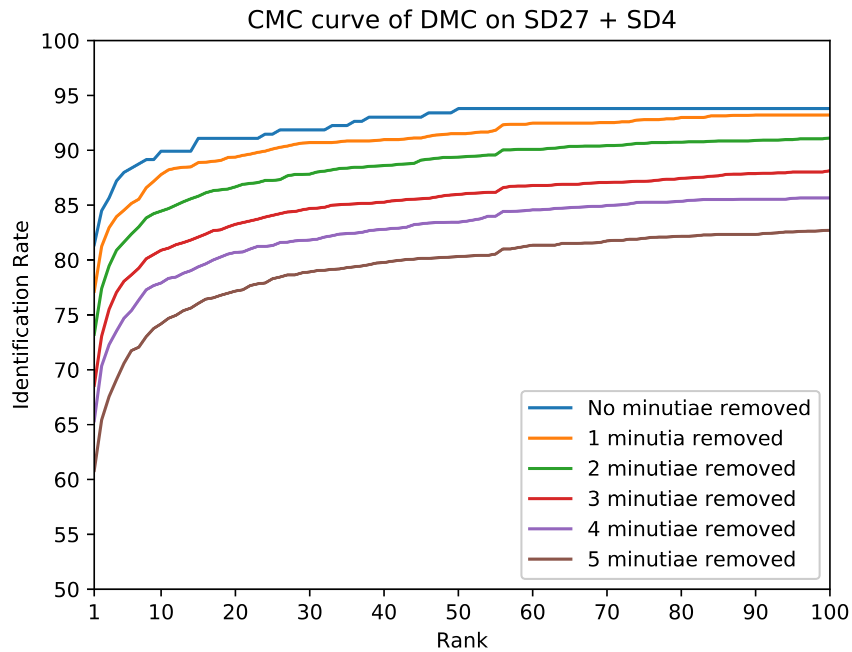

Figure 3.2: CMC curve of NIST SD27 using a background database of NIST SD27 + NIST SD4. This experiment was performed using the DMC matcher when removing a specific number of minutiae from each fingerprint.

3.2.2 Matching score when removing all possible combinations of one, two, and three minutiae

In this subsection we present how the matching score of latent fingerprints behaves when removing all possible combinations of one, two, and three minutiae.

Tables 3.2, 3.3, and 3.4 show on how many instances removing a set of minutiae caused the matching score of the fingerprint to go down or up, for all three cases of removing one, two, and three minutiae. These tables include the results for both matchers used in our experiments.

When only removing one minutia, it is more likely that the matching score of a fingerprint will go down. Table 3.2 shows that for the DMC matcher, in 61.51% of the cases when one minutia was removed, the matching score went down. For the MCC matcher this was in 67.41% of the cases.

When removing all possible combinations of two minutiae we found that in most cases, removing two minutiae resulted in a decrease in matching score, for both algorithms. Results in table 3.3 show that for the DMC algorithm, when two minutiae are removed, the matching score goes down in 68.08% of the cases. With the MCC algorithm the matching score goes down in 78.52% of the cases when two minutiae are removed.

Finally, when removing all possible combinations of three minutiae, it is also more likely that the matching score of the fingerprint goes down for both algorithms. Table 3.4 shows that when using the DMC matcher and removing three minutiae, the matching score goes down in 71.52% of the cases. For the MCC matcher, it goes down in 86.28% of the cases.

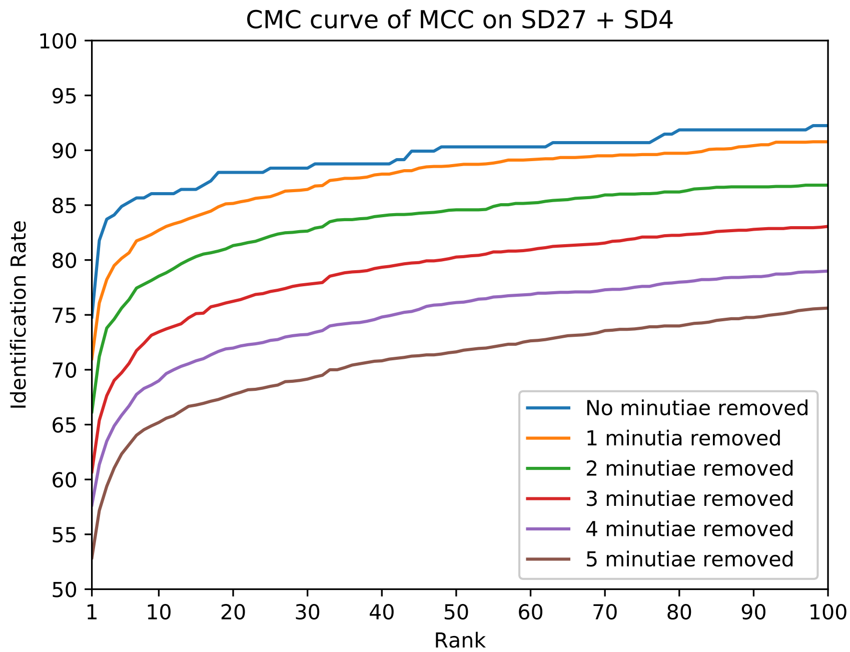

Figure 3.3: CMC curve of NIST SD27 using a background database of NIST SD27 + NIST SD4. This experiment was performed using the MCC matcher when removing a specific number of minutiae from each fingerprint.

Minutiae sets of size 1		
DMC Matcher		
Type	**Count**	**Percentage**
Up in score	2,017	38.49%
Down in score	3,224	61.51%
Total	5,241	
MCC Matcher		
Type	**Count**	**Percentage**
Up in score	1,708	32.59%
Down in score	3,533	67.41%
Total	5,241	

Table 3.2: Number of instances in which removing one minutia caused an increase or a decrease in rank for the DMC and MCC matchers.

When removing minutiae from a latent fingerprint, it is more likely that the matching score of the latent fingerprint with its corresponding impression will go down rather than go up. This is the case for all three cases (removing one, two, and three minutiae), and for both matchers.

Additionally, we can see that it is more likely that the matching score of a latent fingerprint will decrease when removing more minutiae. For example, in the DMC matcher when

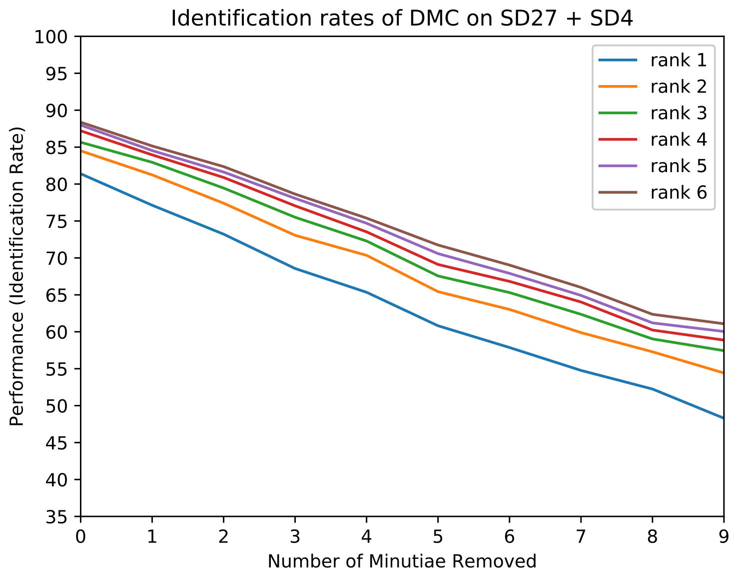

Figure 3.4: Identification rates of the NIST SD27 using a background database of NIST SD27 + NIST SD4 when removing a specific amount of minutiae when using the DMC matcher. Identification rate is plotted against number of minutiae, and the different colored lines represent rank-n identification points.

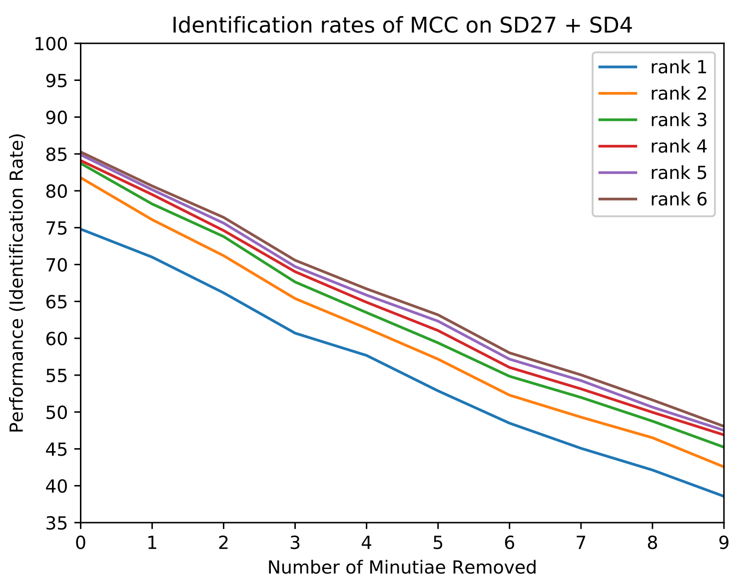

Figure 3.5: Identification rates of the NIST SD27 using a background database of NIST SD27 + NIST SD4 when removing a specific amount of minutiae when using the MCC matcher. Identification rate is plotted against number of minutiae, and the different colored lines represent rank-n identification points.

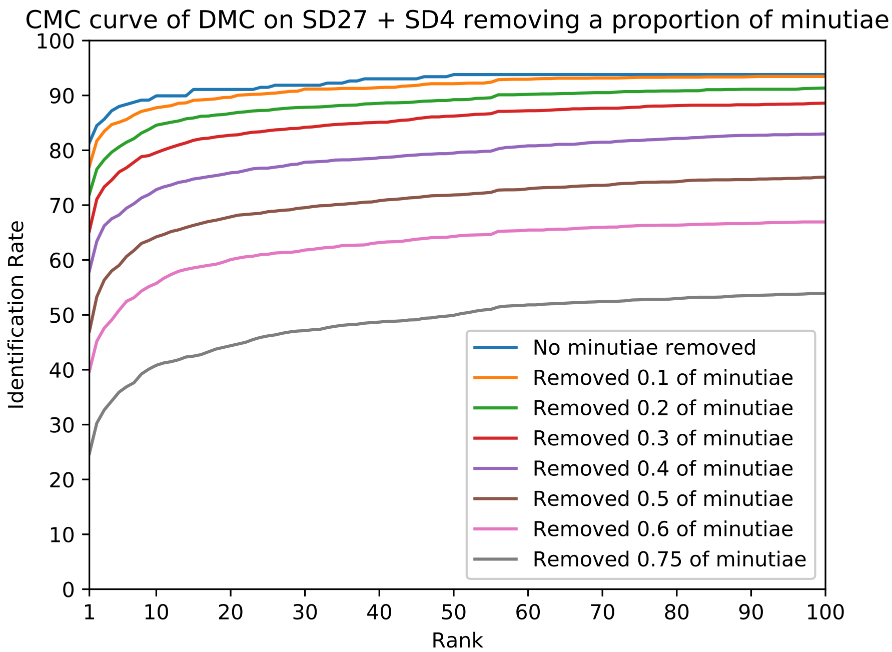

Figure 3.6: CMC curve of NIST SD27 using a background database of NIST SD27 + NIST SD4. This experiment was performed using the DMC matcher when removing a proportion of minutiae from each fingerprint.

Minutiae sets of size 2		
DMC Matcher		
Type	**Count**	**Percentage**
Up in score	23,674	31.92%
Down in score	50,499	68.08%
Total	74,173	
MCC Matcher		
Type	**Count**	**Percentage**
Up in score	15,935	21.48%
Down in score	58,238	78.52%
Total	74,173	

Table 3.3: Number of instances in which removing two minutiae caused an increase or a decrease in rank for the DMC and MCC matchers.

removing one minutia the matching score went down in 61.51% of the cases, when removing two minutiae the score went down in 68.08% of the cases, and when removing three minutiae the matching score went down in 71.52% of the cases.

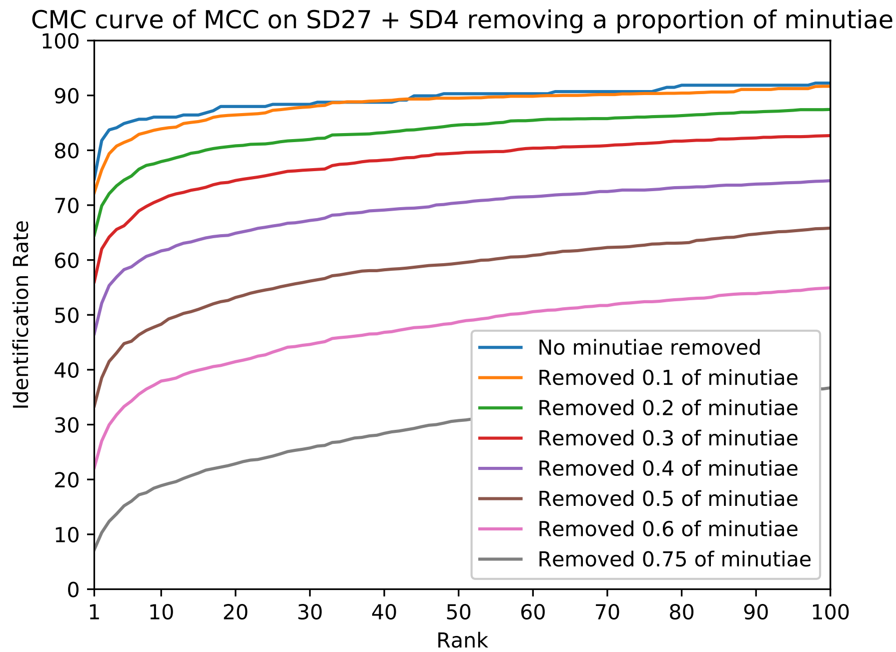

Figure 3.7: CMC curve of NIST SD27 using a background database of NIST SD27 + NIST SD4. This experiment was performed using the MCC matcher when removing a proportion of minutiae from each fingerprint.

Minutiae sets of size 3		
DMC Matcher		
Type	**Count**	**Percentage**
Up in score	266,383	28.48%
Down in score	669,094	71.52%
Total	935,477	
MCC Matcher		
Type	**Count**	**Percentage**
Up in score	128,359	13.72%
Down in score	807,118	86.28%
Total	935,477	

Table 3.4: Number of instances in which removing three minutiae caused an increase or a decrease in rank for the DMC and MCC matchers.

3.2.3 Evaluating the three best and three worst combinations of minutiae

In this subsection, we present the results from evaluating the versions of the fingerprints created by removing the most influential combinations of minutiae in a fingerprint.

Table 3.5 shows a summary of the results of the closed set comparison experiment performed when removing the most influential combinations of one minutia. We have defined two classes; a class “Higher”, which are those minutiae sets from the most influential minutiae sets which had the largest positive impact (or lowest negative impact) in matching score when removed. A second class “Lower” represent all the minutiae sets from the most influential minutiae sets that had the largest negative impact (or smallest positive impact) on matching score when removed. The “Sum” class is the sum of both the “Higher” and “Lower” classes. There are three results columns. The column “Same Rank” shows how many minutiae sets did not affect their fingerprint’s rank when removed. “Up in rank” shows how many minutiae sets increased that fingerprint’s rank when removed. Finally, “Down in Rank” shows how many minutiae sets lowered their fingerprint’s rank when removed.

Table 3.6 shows a similar table but for minutiae sets of size 2. Table 3.7 shows a similar table but for minutiae sets of size 3.

Minutiae sets of size 1			
DMC Matcher			
Class	**Same Rank**	**Up in Rank**	**Down in Rank**
Higher	607 (81.92%)	109 (14.71%)	25 (3.37%)
Lower	517 (69.77%)	19 (2.56%)	205 (27.67%)
Sum	1124 (75.84%)	128 (8.64%)	230 (15.52%)
MCC Matcher			
Class	**Same Rank**	**Up in Rank**	**Down in Rank**
Higher	598 (80.70%)	102 (13.77%)	41 (5.53%)
Lower	472 (63.70%)	5 (0.67%)	264 (35.63%)
Sum	1070 (72.20%)	107 (7.22%)	305 (20.58%)

Table 3.5: Results of the closed set comparison experiment when removing the most influential sets of minutiae of size 1. The “Higher” class include the minutiae sets with the largest positive impact (or smallest negative impact) on matching score when removed. The “Lower” class are the minutiae sets with the largest negative impact (or smallest positive impact) when removed.

As we can see in table 3.5, most fingerprints stay at the same rank when removing one minutia. However, minutia from the class “Higher” are more likely to cause an increase in rank when removed, rather than a decrease. Minutia from the class “Lower” are more likely to cause a decrease in rank when removed rather than an increase.

Minutiae sets of size 2 behave similarly to minutiae sets of size 1. Table 3.6 shows that when removing 2 minutiae from a fingerprint, most fingerprints will retain their same rank. However, as with minutiae sets of size 1, minutiae sets from the class “Lower” are more likely to cause a decrease in rank rather than an increase, and minutiae sets from the class “Higher” are more likely to cause an increase in rank rather than an increase.

Even though minutiae sets of size 1 and 2 tend to behave in the same manner, we can see that minutiae sets of size 2 cause a decrease in rank more frequently compared to minutiae sets of size 1 (21.76% compared to 15.52%).

Finally, minutiae sets of size 3 follow a similar trend as those of sizes 1 and 2. Table 3.7 shows, once again, that most minutiae sets of size 3 do not cause a change in rank when removed. And, similar to minutiae sets of sizes 1 and 2, minutiae sets from the class “Lower”

Minutiae sets of size 2			
DMC Matcher			
Class	**Same Rank**	**Up in Rank**	**Down in Rank**
Higher	610 (84.02%)	111 (15.29%)	5 (0.69%)
Lower	406 (55.92%)	9 (1.24%)	311 (42.84%)
Sum	1016 (69.97%)	120 (8.26%)	316 (21.76%)
MCC Matcher			
Class	**Same Rank**	**Up in Rank**	**Down in Rank**
Higher	592 (81.54%)	106 (14.60%)	28 (3.86%)
Lower	372 (51.24%)	0 (0.00%)	354 (48.76%)
Sum	964 (66.39%)	106 (7.30%)	382 (26.31%)

Table 3.6: Results of the closed set comparison experiment when removing the most influential sets of minutiae of size 2. The "Higher" class include the minutiae sets with the largest positive impact (or smallest negative impact) on matching score when removed. The "Lower" class are the minutiae sets with the largest negative impact (or smallest positive impact) when removed.

Minutiae sets of size 3			
DMC Matcher			
Class	**Same Rank**	**Up in Rank**	**Down in Rank**
Higher	588 (84.12%)	107 (15.31%)	4 (0.57%)
Lower	304 (43.49%)	6 (0.86%)	389 (55.65%)
Sum	892 (63.81%)	113 (8.08%)	393 (28.11%)
MCC Matcher			
Class	**Same Rank**	**Up in Rank**	**Down in Rank**
Higher	573 (81.97%)	99 (14.16%)	27 (3.86%)
Lower	273 (39.06%)	1 (0.14%)	425 (60.80%)
Sum	846 (60.52%)	100 (7.15%)	452 (32.33%)

Table 3.7: Results of the closed set comparison experiment when removing the most influential sets of minutiae of size 3. The "Higher" class include the minutiae sets with the largest positive impact (or smallest negative impact) on matching score when removed. The "Lower" class are the minutiae sets with the largest negative impact (or smallest positive impact) when removed.

are more likely to cause a decrease in rank rather than an increase, and minutiae sets from the class "Higher" are more likely to cause an increase in rank rather than an increase.

In this last case, minutiae sets from size 3 tend to cause a drop in rank more frequently than sizes 1 and 2 when removed (28.11% compared to 15.52% for size 1 and 21.76% for size 2).

Another observation, in all three cases, is that minutiae sets from the class "Lower" are more likely to cause a drop in rank when removed than minutiae sets from the class "Higher" are likely to cause an increase in rank. We believe that this is because many fingerprints are already rank-1, and this cannot be improved even with increasing the matching score.

Figure 3.8 shows a histogram representing how many minutiae sets had lowered rank and by how much in the closed set comparison experiment for all three sizes of sets using the DMC matcher. Figure 3.9 shows a similar histogram but using the MCC matcher.

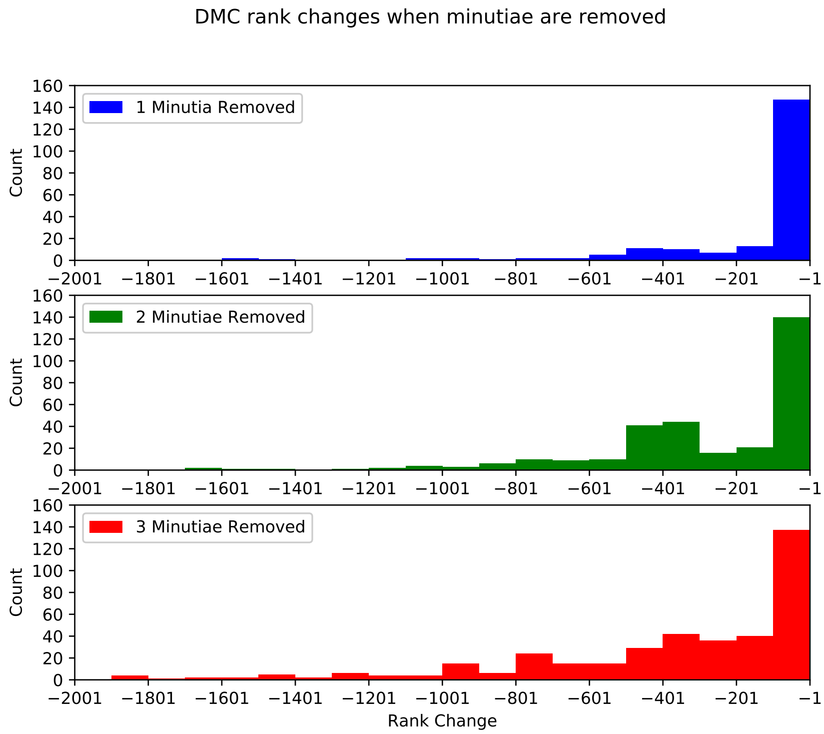

Figure 3.8: Histogram of minutiae sets that had lowered rank in the closed set comparison experiment for the DMC matcher.

The histograms show that for both matchers, there are cases in which removing either one, two, or three minutiae from latent fingerprint causes a drop in rank. Most of the drops in rank are within the first hundred ranks. There are some cases where removing minutiae causes a drastic drop in rank. This is more frequent when removing two or three minutiae, but it also happens when removing one single minutia.

3.2.4 Classifiers on Minutiae Dataset

For this experiment, we compare the results of eight different classifiers on our minutiae dataset. Figure 3.10 shows a bar graph comparing the average AUC of each supervised classifier when using five-fold distribution balanced stratified cross-validation.

From figure 3.10 we can see that PBC4cip [21] had the best performance with an AUC of .608, closely followed by FLDA and Random Forest [3]. These results show that a classifier can predict if a minutia will increase or decrease the matching score of a fingerprint based on the relation of a specific minutia with other minutiae in the fingerprint with a better than random AUC.

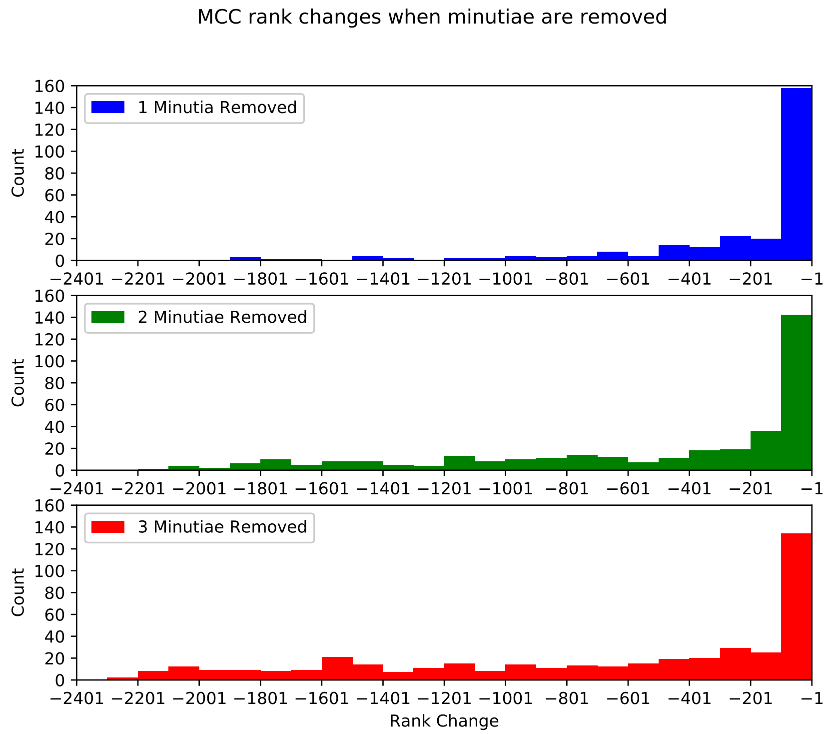

Figure 3.9: Histogram of minutiae sets that had lowered rank in the closed set comparison experiment for the MCC matcher.

3.3 Conclusions

With our experiments, we simulate human error. Specifically, we simulate a human latent examiner failing to mark real minutiae in a latent fingerprint.

By randomly removing both a fixed amount of minutiae and a proportion of the minutiae of all the latent fingerprints in the dataset, we attempted to determine how latent fingerprint identification algorithms behave when minutiae are missing. We believed that the performance of the latent fingerprint matchers would go down, and this was confirmed by our first experiment. Our first experiment also suggested that even removing one minutia could cause a drop in latent fingerprint identification performance.

By counting the instances in which the matching score of a latent fingerprint with its corresponding impression went down when removing minutiae, we determined that it is more likely that the matching score will go down rather than up when removing minutiae. The more minutiae are removed from a fingerprint, the more likely this is. We also determined that it is possible for the matching score to go up when removing minutiae, not only down.

The data we gathered by removing all possible combinations of one, two, and three minutiae was used to find the most influential combinations of minutiae, and perform a closed set comparison experiment with them, as well as to create a dataset which was used to evaluate several machine learning models which attempt to predict if a minutia will have a positive or negative impact in matching score.

Our experiment with the most influential combinations of minutiae showed that, in some

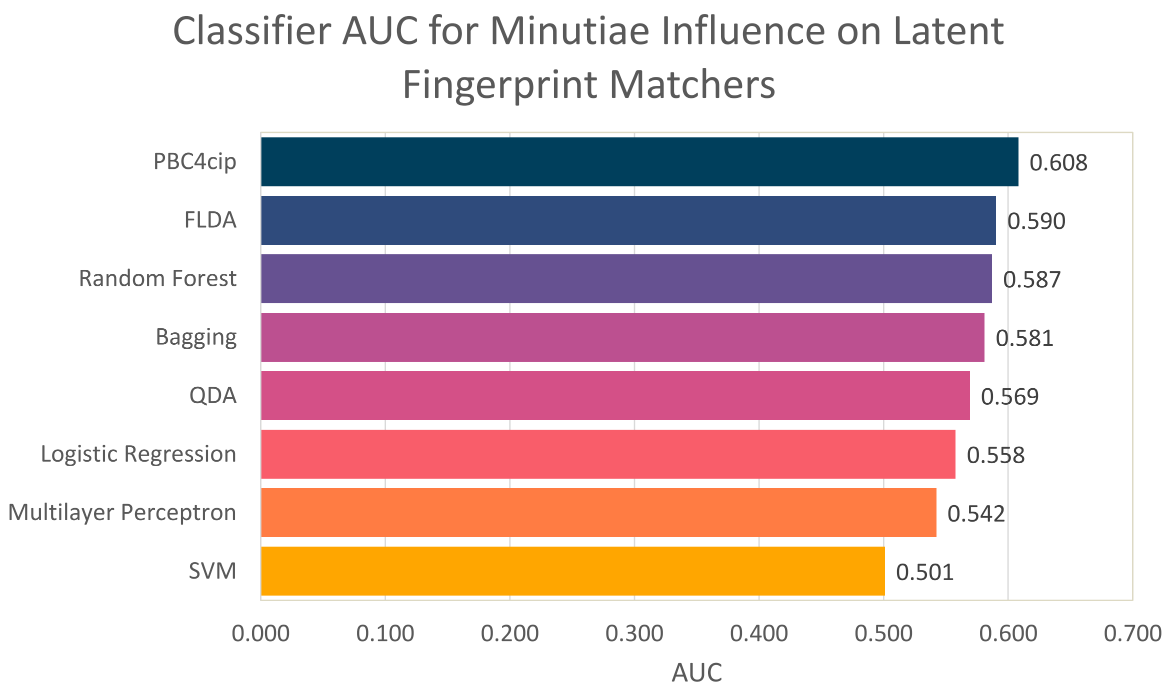

Figure 3.10: Average AUC for eight different classifiers tested on our minutiae dataset.

cases, removing even one minutia could cause a fingerprint not to be identified. This leads us to believe that even one simple human mistake of failing to mark a minutia could cause a latent fingerprint to not be identified. This is why a system that helps human examiners make fewer mistakes is desirable.

With our machine learning experiment, we attempt to create a system that would help human examiners make fewer mistakes. By training several models and calculating the AUC of such models on our generated dataset, we have proven that such a system could exist. Our proposed models can determine how a fingerprint's matching score will change when marking minutiae in real-time.

Our top-performing model, which uses PBC4cip, scored a .608 AUC on our dataset, which only includes data from all possible combinations of minutiae when one minutia is removed. We believe that further research concerning all possible combinations of sizes 2 and 3 could yield better results. Additionally, we believe that designing different features, for example, features that take into account ridge geometry and fingerprint type, could yield better results.

There has not been such an extensive study on the effects of missing minutiae on latent fingerprint identification algorithms up until this thesis. The information presented by this thesis and our initial approaches can serve as inspiration for future work, especially work in which a human latent examiner is assisted in their work instead of being replaced.

Chapter 4

Conclusions and Future Work

4.1 Conclusions

Latent fingerprint identification is an extremely important task. Latent fingerprint identification allows law enforcement to solve crimes, as well as to exonerate suspects. Latent fingerprint identification is also a complex task in which human experts can make mistakes. These mistakes can have severe consequences, such as failing to identify a criminal, or worse, have an innocent person accused. State-of-the-art techniques in automatic latent fingerprint identification have still not reached human-level performance either. With all of this in mind, we believe that developing automatic techniques that assist latent human examiners in their job, instead of techniques that attempt to replace them, is desirable.

We have made an argument as to why missing minutiae simulates human error. Our study attempt to simulate human error by removing minutiae from latent fingerprints, and then studying the effects on latent fingerprint matchers.

There have been studies on how human latent fingerprint examiners make mistakes. There is also a study that applies distortions to synthetic fingerprint impressions and then measures the effect of the distortions on three different fingerprint matchers. But there has been no study on the effects of removing minutiae from latent fingerprints and studying the effects of missing minutiae on latent fingerprint matchers.

When removing minutiae from latent fingerprints, the rank-n identification performance of a closed set comparison experiment will go down. This is true for both latent fingerprint matchers we tested. Additionally, when removing minutiae from a latent fingerprint, it is more likely that the matching score of the latent fingerprint with its corresponding impression will go down, rather than up. Our observations show that the more minutiae are removed from a latent fingerprint, the more likely it is that the matching score will go down. However, it is possible that by removing minutiae from a fingerprint, the matching score will go up.

There are cases in which removing even one single minutia can cause a latent fingerprint to not be identified due to the decrease in rank in a closed set comparison experiment. This is analogous to a human latent examiner failing to mark one minutia, causing a latent fingerprint to go unidentified.

With the information gathered by removing all possible combinations of one minutia, we created several classifiers using different machine learning algorithms. The classifiers can determine if a specific minutia will increase or decrease the matching score of the fingerprint, based on features extracted from the relationship of the minutia in question to other minutiae in the fingerprint with a better-than-random performance, which, in the highest case, is .60 AUC.

Up until now, there has not been such an extensive study into the effects of mistakes when marking minutiae in latent fingerprints on latent fingerprint matchers. This thesis has proposed the first method of simulating human mistakes when marking latent fingerprints. This is also the first empirical study that quantifies the effects of missing minutiae in latent fingerprints, in terms of CMC curve and matching score. We also have proposed the first method that could determine how much a fingerprint's matching score will change by marking minutiae in real-time.

By understanding the effects of mistakes, we can attempt to mitigate them. This thesis aims for both objectives, understanding the effects of human error as well as proposing a method that mitigates them.

4.2 Future Work

Our machine learning models are a first approach to creating a system that can help human latent examiners make fewer mistakes and have better performance on their work. We believe that with more data, models with better performance can be created.

We propose using data gathered from removing all possible combinations of two and three minutiae. This could improve the performance of our models. We also believe that the same effect can be achieved by designing better features.

Other future work on this topic may include the effects of other types of mistakes in latent fingerprint matchers, such as the effects of spurious minutiae, or the effects of the variation that may occur in angle and exact location of minutiae when manually marking latent fingerprints.

On a more general note, we propose future work that attempts to aid human latent fingerprint examiners instead of aiming to replace them. Up until now, no latent fingerprint minutiae extraction algorithm can achieve human-level performance. The same is true for latent fingerprint matching algorithms.

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Curriculum Vitae

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