WHAT FINGERMARKS REVEAL ABOUT ACTIVITIES

Anouk de Ronde

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What do the fingermarks on the cover reveal about activities?

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Contents

Summary

Fingermarks have proven to play an important role in forensic science. Based on the ridge detail information present in a fingermark, individualization or exclusion of a donor is possible by comparing a fingermark obtained from a crime scene to a reference fingerprint of a suspect or a reference fingerprint present in a database. In this process, the intrinsic features of a fingermark are used to determine the source of the fingermark. However, in some cases, the source of a fingermark is not argued but the activity that led to the deposition of the fingermark. The question changes from 'Who left the fingermark?' to 'How did the fingermark end up on the surface?' which requires a different assessment of the findings. The aim of this dissertation *What fingermarks reveal about activities* is to determine how fingermarks could provide information about activities in a reliable way, in order to be used in the forensic evidence process. To answer this main research question, several studies were conducted which are described in Chapters 2 to 5 of this dissertation.

Chapter 2 describes the development of a general framework to evaluate fingermarks given activity level propositions. Relevant variables that function as sources of information when evaluating fingermarks given activity level proposition were identified. The variables transfer, persistency, recovery, background levels of fingermarks, location of fingermarks, direction of fingermarks, the area of friction ridge skin that left the mark and pressure distortions are determined to be the variables that need to be taken into account when evaluating fingermarks given activity level propositions. Based on these variables, three Bayesian networks were presented for different evaluations of the fingermarks given activity level propositions in a case example. The first Bayesian network focusses on the evaluation of fingermark patterns present on an item given propositions that dispute a certain activity that was carried out. The second network enables the evaluation of propositions that dispute the source of the activity. The last Bayesian network allows for the evaluation of multiple fingermarks present on an item. The presented networks function as a general framework for the evaluation of fingermarks given activity level propositions, which can be adapted according to specific case circumstances.

Chapter 3 shows how the proposed framework in Chapter 2 can be used in casework by means of a case example. In order to use a Bayesian network, probabilities need to be assigned to the states of the nodes of the Bayesian network. In this study, a case specific experiment with the use of knives was conducted and the resulting data was used to assign probabilities to two Bayesian networks, both focusing on a different use of the experimental data. In the experiment, participants carried out two separate activities with two knives: stabbing and cutting food. The transfer, persistence and recovery probabilities of particular areas of the hand to particular locations on the knife were studied given both activities and used to assign probabilities to the Bayesian networks, followed by an evaluation of fictitious findings in the case example. This study has shown how different uses of the data resulting from a case specific experiment on fingermarks can be used to assign probabilities to Bayesian networks for the evaluation of fingermarks given activity level propositions.

In **Chapter 4**, we focus on the location of fingermarks on an item, one of the variables iden-

tified in Chapter 2 as being an important source of information for activity level evaluations for fingermarks. In this study, we developed a classification model to evaluate the location of fingermarks given activity level propositions based on an experiment with pillowcases. In this experiment, participants carried out two activities with the use of paint on their hands: smothering a victim using a pillow and changing a pillowcase of a pillow. The pillowcases were photographed and translated into grids. Based on a distance measure between the grids, a classification model was created to evaluate the location of the fingermarks present on the pillowcase with regards to the two activities smothering and changing. The results showed that fingermark patterns left on a pillowcase by smothering with a pillow can be well distinguished from fingermark patterns left by changing a pillowcase of a pillow, with an accuracy of 98.8%. The result of this study is a model that can be used to study the location of fingermarks on two-dimensional items in general, for which is expected that different activities will lead to different trace locations.

Chapter 5 investigates the application of the location model presented in Chapter 4 to a dataset of letters, to study whether the model could also be used to distinguish between fingermark patterns left when writing a letter and fingermark patterns left when reading a letter. An experiment was conducted in which participants were asked to read a letter and to write a letter on A4- and A5-sized papers. The fingermarks on the letters were visualized using conventional visualization techniques and the letters were photographed and translated into grids. The classification model presented in Chapter 4 was used to classify the letters into the activities of reading and writing based on the location of the fingermarks on the letters. The results showed that fingermark patterns left by writing a letter can be well distinguished from fingermark patterns left by reading a letter, with an accuracy of 98.0%. The results also showed that the length of the letter and the handedness of the donor did not influence the classification performance. However, the size of the paper and an additional activity of folding the paper after writing on it decreased the model accuracy significantly (64.4%). Based on the results of this study, it can be concluded that the model proposed in Chapter 4 is indeed applicable to other objects for which it is expected that different activities lead to different fingermark locations, given the condition that the training set is representative for the object to be tested with regards to the size of the object and the activity that was carried out with the object.

This dissertation supports the view that fingermarks contain valuable information about the activity that caused the deposition of the fingermarks. By the development of a general framework which can be used to evaluate fingermarks given activity level propositions, the design of a measurement method to evaluate the location of fingermarks given activity level propositions, and by showing the applications and limitations of these methods, the forensic community is provided with reliable methods that can be used when evaluating fingermarks given activity level propositions.

Samenvatting

Vingersporen worden gezien als een belangrijk bewijsmiddel binnen de forensische opsporing. Op basis van de details in de papillairlijnen van een vingerspoor is het mogelijk om een donor te individualiseren of uit te sluiten door een vingerspoor dat gevonden is op een plaats delict te vergelijken met de vingerafdrukken van een specifieke verdachte of met vingerafdrukken die zijn opgeslagen in een databank. Tijdens dit proces worden de intrinsieke eigenschappen van een vingerspoor gebruikt om de donor van het spoor te individualiseren. Echter, in sommige gevallen staat de donor van het vingerspoor niet ter discussie, maar is het de vraag welke activiteit ten grondslag ligt aan het achtergelaten vingerspoor. De vraag verandert van 'Wie heeft het vingerspoor achtergelaten?' naar 'Hoe is het vingerspoor op het oppervlak terecht gekomen?', waarvoor een andere analyse van de sporen noodzakelijk is. Het doel van dit proefschrift *What fingermarks reveal about activities* is om te bepalen hoe vingersporen betrouwbare informatie kunnen geven over de activiteit die heeft plaatsgevonden toen het vingerspoor werd achtergelaten, zodat deze informatie gebruikt kan worden binnen het forensische onderzoeksproces. Om deze vraag te beantwoorden zijn er verschillende studies uitgevoerd, die zijn beschreven in hoofdstuk 2 t/m 5 van dit proefschrift.

In **Hoofdstuk 2** wordt de ontwikkeling van een generalistisch framework voor het evalueren van vingersporen op activiteitniveau beschreven. Eerst zijn de relevante variabelen geïdentificeerd die mogelijk informatie geven over de relatie tussen de vingersporen en de activiteiten die hebben plaatsgevonden. De variabelen overdracht, persistentie, visualisatie, de aanwezigheid van vingersporen op de achtergrond, locatie, richting, welk deel van de hand het spoor heeft achtergelaten en verstoringen als gevolg van uitgevoerde druk op het oppervlak zijn geïdentificeerd als belangrijke informatiebronnen voor vingersporen op activiteitniveau. Met behulp van deze variabelen zijn drie Bayesiaanse netwerken gebouwd voor een casusvoorbeeld, om op verschillende manieren de vingersporen op activiteitniveau te kunnen analyseren. In het eerste netwerk ligt de focus op een greep die geanalyseerd wordt met proposities waarin de activiteit ter discussie staat. Bij het tweede netwerk ligt de focus op een greep die geanalyseerd wordt met proposities waarin de persoon die de activiteit uitvoert ter discussie staat. Met het laatste netwerk kunnen meerdere grepen op een voorwerp geanalyseerd worden. De drie netwerken vormen een basis voor de evaluatie van vingersporen op activiteitniveau, waarbij de netwerken kunnen worden aangepast naar casus specifieke omstandigheden.

Hoofdstuk 3 laat zien hoe het voorgestelde framework in Hoofdstuk 2 gebruikt kan worden aan de hand van een zaaksvoorbeeld. Om een Bayesiaans netwerk te kunnen gebruiken, moeten kansen worden toegekend aan de staten van de knopen van een Bayesiaans netwerk. In deze studie hebben we een casus specifiek experiment uitgevoerd om kansen te kunnen toekennen aan twee Bayesiaanse netwerken, waarbij ieder Bayesiaans netwerk een andere toepassing van de experimentele data laat zien. Hiertoe is een experiment met messen uitgevoerd waarin deelnemers twee verschillende activiteiten hebben uitgevoerd: het steken met een mes en het snijden van eten met een mes. De overdrachtskansen van bepaalde delen van de hand op bepaalde delen van het mes tijdens deze twee activiteiten zijn geanalyseerd en gebruikt om kansen aan

het Bayesiaanse netwerk toe te kennen, waarna een evaluatie is uitgevoerd voor fictieve bevindingen in de voorbeeld casus. Deze studie laat zien hoe casus specifieke experimenten kunnen worden gebruikt om kansen te bepalen voor een Bayesiaans netwerk, om vervolgens het netwerk te kunnen gebruiken bij het evalueren van vingersporen op activiteitniveau.

In **Hoofdstuk 4** ligt de focus op een van de variabelen die in Hoofdstuk 2 is aangemerkt als belangrijke bron van informatie voor een analyse van vingersporen op activiteitniveau: de locatie van de vingersporen. In dit onderzoek hebben we een classificatie model ontworpen om de locatie van vingersporen te analyseren op activiteitniveau, gebaseerd op een experiment met kussenslopen. In dit experiment hebben deelnemers twee activiteiten uitgevoerd met verf op hun handen: het smoren met een kussen en het verschonen van een kussen. De kussenslopen zijn gefotografeerd en omgezet naar rasters. Op basis van een afstandsmaat tussen de rasters is een classificatiemodel ontworpen waarmee een voorspelling van de activiteit smoren of verschonen kan worden gemaakt op basis van de locatie van de vingersporen op de kussensloop. De resultaten laten zien dat er, op basis van de locatie van de vingersporen op een kussensloop, goed onderscheid gemaakt kan worden tussen het vingersporenbeeld achtergelaten op het kussensloop door smoren met een kussen en het vingersporenbeeld achtergelaten op het kussensloop door het opmaken van een kussen, met een nauwkeurigheid van 98.8%. Het resultaat is een model dat gebruikt kan worden om de locatie van vingersporen te kunnen analyseren op activiteitniveau. Daarnaast verwachten we dat het model ook gebruikt kan worden voor de analyse van de vingersporenlocatie op andere tweedimensionale voorwerpen waarvan verwacht wordt dat verschillende activiteiten leiden tot verschillende locaties van de vingersporen op het voorwerp.

In **Hoofdstuk 5** wordt onderzocht of het model dat ontworpen is in Hoofdstuk 4 ook toegepast kan worden op brieven om onderscheid te maken tussen het schrijven en het lezen van een brief. In een experiment hebben verschillende deelnemers een brief gelezen en een brief geschreven op A4 en A5 papier. De vingersporen op de brieven zijn zichtbaar gemaakt met behulp van conventionele visualisatie technieken en de brieven zijn gefotografeerd en omgezet naar rasters. Het classificatie model uit Hoofdstuk 4 is gebruikt om de brieven te classificeren in de categorieën schrijven of lezen, op basis van de locatie van de vingersporen op de brieven. Uit de resultaten blijkt dat het vingersporenbeeld dat achtergelaten wordt bij het schrijven van een brief goed onderscheiden kan worden van het vingersporenbeeld dat achterlaten wordt bij het lezen van een brief, met een nauwkeurigheid van 98.0%. Uit de resultaten blijkt ook dat de lengte van de brief en links- of rechtshandigheid van de donor geen invloed heeft op de classificatie prestatie van het model. De afmeting van het papier en een extra activiteit zoals het vouwen van het papier na het schrijven van de brief laten echter wel zien dat de classificatie prestatie van het model afneemt (64.4%). Op basis van de resultaten van deze studie kunnen we concluderen dat het model gepresenteerd in Hoofdstuk 4 inderdaad toegepast kan worden op andere voorwerpen waarvan verwacht wordt dat verschillende activiteiten leiden tot verschillende vingerspoor locaties op het voorwerp, met de kanttekening dat de objecten in de training set representatief moeten zijn voor het object dat getest wordt met betrekking tot de afmetingen van het voorwerp en de activiteiten die ermee zijn uitgevoerd.

Dit proefschrift laat zien dat vingersporen inderdaad waardevolle informatie bevatten over de activiteiten waardoor ze zijn veroorzaakt. Met het ontwerpen van een generalistisch framework dat gebruikt kan worden voor het evalueren van vingersporen op activiteitniveau, het ontwikkelen van een methode om de locatie van vingersporen te analyseren op activiteitniveau en

het testen en toepassen van deze methodes in praktijkvoorbeelden hebben we betrouwbare methodes ontwikkeld waarmee vingersporen op activiteitniveau geëvalueerd kunnen worden binnen het forensisch onderzoeksproces.

1

Introduction

1

1.1. Fingermarks as forensic evidence

Fingermarks are widely recognized as forensic evidence in criminal investigations for identification purposes. When a hand touches a surface, material may be transferred from the hand to the surface, leaving a characteristic fingermark pattern [1]. Based on assumptions about the uniqueness of the friction ridge skin patterns present on the skin, these fingermarks may be used to identify the donor [2]. Consequently, fingermarks are often used to provide a link between the donor and the crime scene.

In some cases, determining the source of a fingermark may not be sufficient to address the relevant question in court [3]. For example, in homicide cases in which a suspect and a victim share the same household, the presence of the suspect's fingermarks on a knife that is used to stab the victim do not inevitably mean that the suspect stabbed the victim. There might be a reasonable alternative explanation for the presence of the suspect's fingermarks on the knife. In cases like this, the question in court changes from 'Who is the source of the fingermarks?' to 'What activity led to the deposition of the fingermarks?', which requires a different assessment of the findings. Additional information about other factors such as the location of the fingermarks on the knife, the orientation of these fingermarks or the time of deposition is needed to link the fingermarks to the questioned activity of stabbing (Figure 1.1).

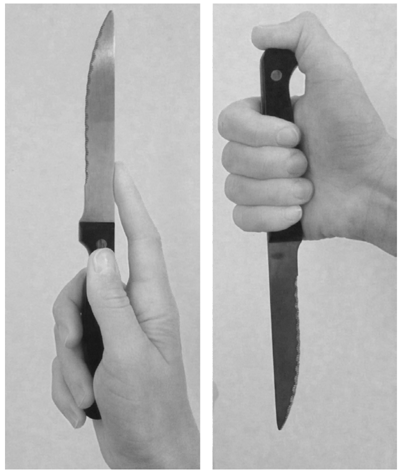

Figure 1.1: Potential orientation of the hand on a knife as a result of different activities. Left: knife being held to use for cutting food. Right: knife being held to use for stabbing.

To date, no research has been carried out that addresses how to evaluate fingermarks in relation to disputed activities, even though for other types of evidence, such as fibers, glass and DNA, this is a widely-explored topic [4]. The aim of this thesis is to study how fingermarks can provide information about the activity that is carried out. Is there a way in which we can retrieve information from the fingermarks about what has happened on the crime scene and how can we determine the evidential value of this information?

1

1.2. The basics of fingerprints

Human hands and feet are covered with friction ridge skin. This friction ridge skin is formed by friction ridges present on the surface skin, that already appear during fetal development [2]. Due to the secretion of eccrine and sebaceous compounds by the skin and the presence of possible environmental contaminants on the skin, a potential transfer of material takes place when a finger comes in contact with a surface, often in a characteristic fingerprint pattern [5]. These fingermarks may appear as visible fingermarks or latent fingermarks, which first have to be visualized using an enhancement technique.

There are many different techniques that can be used to visualize fingermarks on a surface. These techniques fall into three types of treatments: optical treatments based on illuminating the fingermark using a light source, physical treatments based on powders to visualize the fingermark or chemical treatments based on a chemical reaction with the components of a fingermark[1]. The choice of the type of treatment may be a difficult task, especially since the composition of a fingermark may change from the time of deposition to the subsequent recovery due to a degradation process [5]. The degradation process is affected by the 'triangle of interaction' [1], shown in Figure 1.2. The composition of the fingermark, the environment, the surface and the interactions between them influence the process of fingermark degradation and these factors therefore function as sources of information to determine the most appropriate enhancement technique to visualize the fingermarks [6].

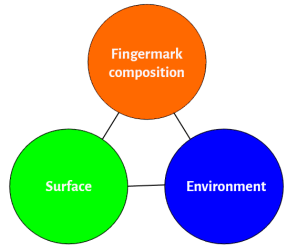

Figure 1.2: Triangle of interaction. Figure adapted from Bleay et al. [1]

The friction ridges appear in complex patterns, and based on the assumption that every person holds a unique pattern of friction ridge skin on their hands, the ridge detail information of the friction ridges can be used as a source for individualisation [1]. Three levels of detail are distinguished [7]: Level 1 detail consists of general morphological information represented by the general pattern that is present in a fingerprint. Level 2 detail consists of the features that are visible in the flow of the ridges, also called minutiae, as shown in Figure 1.3. Level 3 detail includes features within the ridges, such as the pores, edge shapes and discontinuities within the ridges. All three levels of detail are used to draw conclusions on the identity of the donor of a fingermark. This can be done by a direct comparison between a fingermark found on the crime scene and a reference fingerprint from a possible donor, or by a search against a database.

[1] A detailed description of the available enhancement techniques is described by Bleay et al. [1] and Champod et al. [2].

Figure 1.3: Fingerprint showing two clusters of minutiae. Figure adapted from Champod et al. [2].

1.3. Hierarchy of propositions

When investigating forensic evidence, a forensic scientist formulates a pair of propositions which represent the prosecution hypothesis (H_p) and the defense hypothesis (H_d) [8]. With the help of these propositions, the forensic scientist determines a likelihood ratio by calculating the ratio of the probabilities of observing the evidence (E) given the two propositions and the relevant case information (I):

$$LR = \frac{Pr(E|H_p, I)}{Pr(E|H_d, I)} \tag{1.1}$$

According to Cook et al. [9], three levels of propositions are distinguished: source, activity and offense level propositions. Source level propositions relate to the source of the evidential material. For fingermarks, source level propositions question the source of the fingermark or whether two fingermarks originate from the same source, and the patterns in the friction ridge skin form the primary source of information. Activity level propositions relate to the activities that must have taken place during the deposition of the evidential material. This type of propositions usually address questions regarding how and when evidence ended up on a surface. Relevant case information is required for the evaluation of activity level propositions, such as information about the transfer, persistence and recovery of the fingermarks, but also the location or the direction of the fingermarks. Offense level propositions relate to the actual crime. These propositions are usually considered by the judiciary during a criminal trial. Examples of the hierarchy of propositions for fingermarks are shown in Figure 1.4.

Generally, a higher level of propositions results in a greater assistance of the scientific evidence in court [9]. Using source level propositions to determine the source of a fingermark will often not aid the court in determining what activities were carried out during the deposition of the fingermark on the crime scene. A shift to activity level propositions is required, especially when expert knowledge is essential to understand the scientific findings in relation to the questioned activities [10]; knowledge that is most probable not available to the judiciary in court. By failing to acknowledge this shift by using only source level propositions in these cases, the forensic scientist leaves the evaluation of the findings at activity level to the judiciary, who may not have the knowledge that is needed to address these questions [11].

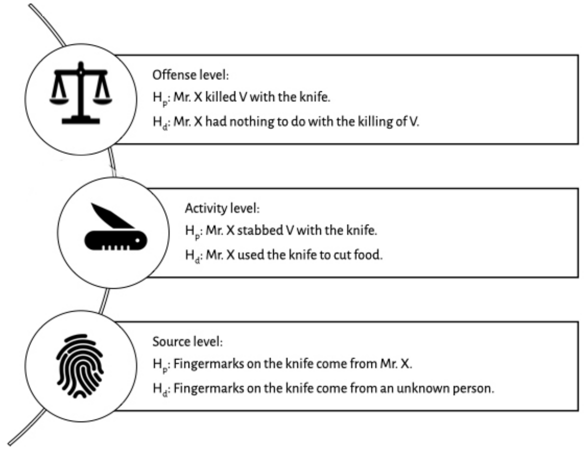

Figure 1.4: Example of the hierarchy of propositions for fingermarks.

1.4. Bayesian networks

For the interpretation of evidence given activity level propositions, contextual information which leads to a 'framework of circumstances' is essential [9]. In case multiple variables influence the interpretation of the evidence, possible dependencies between these variables may complicate a direct calculation of the likelihood ratio to determine the evidential value [12]. A method that is commonly used to evaluate findings when additional dependencies between relevant variables play a role is a Bayesian network [4].

A Bayesian network is a graphical representation of assumed dependencies and influences between a set of variables which can be used to directly calculate a likelihood ratio for observed findings. This model is particularly useful if there are dependencies between relevant variables in place that play part in the evaluation of scientific evidence [13]. A Bayesian network consists of nodes, states, directed arcs and probability assignments. The nodes represent the relevant variables which can take possible values or categories, denoted by the states of the node. The directed arcs between the nodes represent the dependencies between the variables. The probability for the occurrence of the states of a node are described in its probability assignment. If a directed arc is pointed from node A to node B, node A is considered to be the parent node of node B, the child node. The probability for the occurrence of the states of a child node is dependent on the occurrence of the states of its parent nodes, which is described by conditional probabilities in the probability assignment for a child node. The probability assignment for a parent node contains unconditional probabilities. The nodes and directed arcs are combined into a directed acyclic graph (DAG), a network in which no loops are permitted [14]. Due to the structure of the network, the effect of new evidence on the probabilities of the states of the nodes of the network can be directly computed [4]. Therefore, a Bayesian network can be used to compute a likelihood ratio for the evidence given the prosecution proposition and the defence proposition, based on the totality of the evidence. This makes Bayesian networks an appropriate method to evaluate evidence given activity level propositions within the field of forensic science [15].

Aitken and Gammerman [12] were the first to propose the use of Bayesian networks for the evaluation of forensic evidence. After this introduction, Bayesian networks were mainly applied for the purpose of determining the source of a trace [15, 16]. Evett et al. [17] were the first to suggest the use of Bayesian networks for the evaluation of activity level propositions for small quantities of DNA. Nowadays, Bayesian networks are used to evaluate evidence given activity level propositions for the forensic expertise fields of DNA, fibres, glass, paint and gunshot residues [4]. Although Bayesian networks have been proposed to evaluate fingermarks given source level propositions [18], the use of Bayesian networks for the evaluation of fingermarks given activity level propositions is currently not addressed in scientific literature.

1.5. Thesis aims

At the start of this research, the evaluation of activity level propositions for fingermarks is an unexplored territory. During criminal investigations, information about activities that are potentially carried out on a crime scene is used to determine where to search for fingermarks. If, as a result, fingermarks are recovered, the fingermarks are solely used for identification purposes. Considering the direct relation between touching a surface and the deposition of a fingermark, it is expected that fingermarks could potentially provide a source of information for the movements and activities that were carried out on a crime scene. This leads to the central research question: *How can we derive information about activities from fingermarks in a reliable way, in order to be used in the forensic process?* In order to answer this question, the research is divided into two lines of research. For the first line of research, the following sub questions need to be addressed:

- Currently, there is no method available for the evaluation of fingermarks in relation to different activities. How can we derive a general framework which can be used to evaluate fingermarks given activity level propositions?
- To be able to use the proposed framework, probabilities need to be assigned to the states of the nodes of a Bayesian network. How can data from case-specific experiments be used in the proposed framework to be able to apply a Bayesian network for the evaluation of fingermarks given activity level in actual casework?

The first line of research indicated that the variable location of fingermarks on an object of interest is an important variable to consider when evaluating fingermarks given activity level propositions. The second line of research concentrates on the variable fingermark location. The following sub questions need to be addressed:

- An objective method to measure the location of fingermarks in relation to disputed activities is lacking. How can we develop a model to objectively study the location of fingermarks in relation to activity level propositions?
- The proposed model for the location of fingermarks was developed based on an experiment with pillowcases. In order to find out whether this model is more generally applicable, it needs to be studied what the limitations of the developed model are. Is the proposed model applicable to other objects of interest and what are the limitations of the developed model?

1.6. Thesis outline

The thesis is divided into 6 chapters, of which chapters 2-5 present the different studies that were conducted as part of this dissertation. Chapter 6 provides a general discussion of the results.

Chapter 2 describes the evaluation of fingermarks given activity level propositions by using Bayesian networks. In this study, the key variables that provide information about potential activities that were carried out during the deposition of fingermarks are identified and their current state of knowledge is discussed. Furthermore, three Bayesian networks are constructed for different type of evaluations of a case example. This chapter presents a framework for the evaluation of fingermarks given activity level propositions.

Chapter 3 builds on Chapter 2 and demonstrates how data resulting from case specific experiments can be used to assign probabilities to the states of the nodes of a Bayesian network. Based on the case example of the murder of Meredith Kercher, a Bayesian network is created following the framework presented in Chapter 2. Additionally, an experiment with knives is conducted in which participants used a knife to stab a victim or to cut food. The results are used to assign probabilities to the created Bayesian networks exploring the effect of different uses of the experimental data.

Chapter 4 describes the development of a model to evaluate the location of fingermarks with regards to activity level propositions. For this purpose, an experiment was conducted at the Dutch music festival Lowlands, to test whether the activity of smothering can be distinguished from the activity of changing a pillowcase based on the touch traces that are left on the pillowcase. A binary classification model is created to classify pillowcases into one of the two classes smothering or changing, based on the fingermark locations.

Chapter 5 builds on Chapter 4 by applying the binary classification model to a dataset consisting of letters, to study whether the model could also be used to distinguish the activity of writing a letter from the activity of reading a letter, based on the location of the fingermarks on the letters. Additionally, limitations of the classification model are tested by testing variations in length of the letter, handedness of the donor and size of the paper with an additional activity of folding the paper.

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2

The evaluation of fingermarks given activity level propositions

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ABSTRACT

Fingermarks are highly relevant in criminal investigations for individualization purposes. In some cases, the question in court changes from 'Who is the source of the fingermarks?' to 'How did the fingermark end up on the surface?'. In this chapter, we explore the evaluation of fingermarks given activity level propositions by using Bayesian networks. The variables that provide information on fingermarks given activity level propositions are identified and their current state of knowledge with regards to fingermarks is discussed. We identified the variables transfer, persistence, recovery, background fingermarks, location of the fingermarks, direction of the fingermarks, the area of friction ridge skin that left the mark and pressure distortions as variables that may provide information on how a fingermark ended up on a surface. Using three case examples, we show how Bayesian networks can be used for the evaluation of fingermarks given activity level propositions.

2

2.1. Introduction

Fingermarks play an important role in forensic science. Based on the assumption that every individual holds a unique pattern of friction ridge skin on their hands, this pattern can be used for identification. By determining the source of the fingermark, a link between the donor and a crime scene can be established. There is a wealth of research on the visualization of latent fingerprints in order to enhance the friction ridge pattern for individualization purposes [1, 2]. While this type of research is very valuable for the individualization of the source of a trace, the fingermark itself may not unequivocally be attributed to a criminal activity.

An important question that often comes up in court cases regarding forensic evidence is to determine how or when a trace was deposited. Consider the following case example; a woman calls the police to report that there has been a burglary in her apartment. The police find four fingermarks on the railing of the balcony, which leads to the assumption that the perpetrator entered the apartment via the balcony. Through a database search, a match is found with a suspect, who is an acquaintance of the woman. The suspect claims that, instead of an unauthorized intrusion via the balcony, he visited the woman a week earlier and smoked a cigarette on the balcony while leaning on the railing. In cases like this, the question at stake changes from 'Who is the source of the fingermarks?' to 'What activity led to the deposition of the fingermarks?', which requires a different assessment of the findings.

When investigating forensic evidence, a forensic scientist formulates a set of propositions, usually representing the prosecution and the defense propositions. Cook et al. [3] propose three classes of propositions: source level, activity level and offence level propositions. In the balcony case example, the investigation shifts from determining the source of the fingermarks to addressing the activity that took place. In the forensic expertise fields of DNA, fibers, glass, paint and gunshot residues, evaluation of the evidence given activity level propositions is already being studied [4]. However, for fingermarks, this topic is not yet explored.

There are many variables that may provide information on how a fingermark was deposited on a surface. In the balcony case example, where the question now is whether the suspect climbed the balcony or the suspect smoked a cigarette on the balcony and leaned on the railing, variables such as the location of the fingermarks, and the direction of the fingermarks may provide information on the activity that took place. In general, the interpretation of evidence at activity level requires more contextual information [3]. When multiple variables influence the interpretation of the evidence, it can be difficult to take their dependencies into account in a direct calculation of a likelihood ratio [5].

A method that is commonly used for cases where additional factors play a role is a Bayesian network. A Bayesian network is a graphical representation of a mathematical model which can be used to evaluate the findings, particularly if there is a dependency between relevant variables [4]. A Bayesian network consists of nodes, directed arcs and probability assignments of the nodes. It can for instance be used to compute a likelihood ratio of the evidence given the prosecution proposition and the defense proposition, based on all variables that are considered relevant in the interpretation of the evidence. This makes Bayesian networks an appropriate method to evaluate evidence given propositions at activity level within the field of forensic science. Although Bayesian networks have been proposed to interpret fingermarks given source level propositions [6], they have not been used to evaluate fingermarks given activity level propositions.

In this chapter, we describe a framework for the evaluation of fingermarks given activity level propositions using Bayesian networks. We discuss the variables that provide information on fingermarks at activity level, followed by three case examples for which Bayesian networks are created. We ultimately elaborate on possible directions for further research on this topic such that the proposed framework could be optimally applied in casework.

2.2. Relevant variables

In this section, we explore the variables that provide information on fingermarks with regards to activity level propositions. We do not discuss variables related to source level propositions since determining the donor of a fingermark is considered outside the scope of this study. Furthermore, we assumed that if a fingermark is present, the donor actually touched the item[1]. Touching a surface can be seen as an activity in itself, and therefore activity level propositions may dispute whether the surface is actually touched or the fingermark is a result of forgery [1]. Another dispute may focus on the circumstances of how the fingermark is recovered, for instance when there are issues with the chain of custody [7]. These types of propositions are considered outside the scope of this chapter by assuming the surface is actually touched when a fingermark is present.

We divided the relevant events that provide information on the activity that led to deposition of the fingermarks in two groups of variables: 'fingermark formation process', and 'manner of deposition'. The group 'fingermark formation process' represents the factors that relate to the requirements of fingermark formation, visualization and recovery. The variables identified in this group are the transfer, persistence and recovery of fingermarks and the background levels of fingermarks already present on an item. The group 'manner of deposition' represents the factors that relate to how the donor deposited the fingermark. The variables identified in this group are the position of the hand during placement, the location of the fingermarks, area of friction ridge skin that left the mark, the direction of the fingermarks and the pressure applied to the surface during deposition.

2.2.1. Fingermark formation process

Transfer

A consequence of an activity may be the transfer of material to a surface by a finger, creating a fingermark. Until now, research on the transfer of fingermarks focused mostly on the composition of the residue for the purpose of enhancing the quality of the fingermark for individualization at source level [8]. However, the guidelines of the ENFSI [9] show that transfer is an important variable to consider when looking at the scientific findings in relation to activities.

Fingermarks have advantages over other types of forensic evidence. Fingermarks are considered to be a proof of contact due to a direct transfer of the ridge detail to a surface. Furthermore, fingermarks cannot transfer indirectly via surfaces or individuals unless great effort is made [10]. Secondary or further transfer of fingermarks is generally not taken into account (please note the exception of fingermarks on tape [11]) . These are important advantages over DNA, since DNA can transfer indirectly and even retransfer from one location to another [12]. Although indirect transfer is generally not applicable to fingermarks, transfer is still an important variable to consider since the probability of transfer of a fingermark may differ between activities.

[1] On a crime scene, fingermarks can be found on items and fixed surfaces. In this article, we use the term item for both, unless further specified.

The transfer of fingermarks depends on several factors: the nature of the surface, the deposition conditions and donor characteristics [8, 13, 14]. The deposition conditions such as pressure and duration of contact may vary between activities, and this may result in different transfer probabilities. If the pressure of the hand on the surface is higher, the probability of transfer might be higher [13]. The propositions of the prosecution and the defense may suggest different levels of pressure needed to conduct the proposed activities, leading to the assignment of different transfer probabilities. This is also true for other deposition conditions, which make the observed transfer (or the absence thereof) more or less probable given different propositions. However, the development and recovery of fingermarks on a surface depend on more than the mechanisms of transfer; variables such as persistence and recovery also influence the probability of recovering fingermarks.

Persistence

A fingermark may not be recovered in the same condition as it was deposited. This is due to degradation, the process during which the initial composition of a fingermark changes after deposition [8]. Degradation will occur from the time the fingermark has been deposited, to the subsequent evidence recovery and may affect the persistence of a fingermark. The degradation of a fingermark is influenced by the 'triangle of interaction', consisting of the fingermark composition, the nature of the surface and environmental conditions [2]. For the nature of the surface it is known that fingermark compounds may be absorbed by surfaces of porous material, whereas they stay on the surface of non-porous materials. This surface interaction may influence the degradation of the fingermarks [15]. Furthermore, environmental factors like temperature, light, humidity and air circulation have shown to influence the degradation of fingermarks over time [14].

It is generally not expected that the nature of the surface is disputed between activity level propositions since the same set of fingermarks on the same item is questioned under both propositions (unless there is an issue with the chain-of-custody [7]). However, environmental conditions may vary between a pair of activity level propositions for fingermarks, for example, if propositions dispute the moment when the fingermark is left and thus the time interval between the moment of deposition and recovery. During that time interval, the fingermarks could be subjected to different environmental conditions. In that case, the factor persistence plays a significant role.

Recovery

After transfer to and persistence on a surface, the fingermark must be detected and recovered from the crime scene. This process is described by the variable recovery. Fingermarks can be latent, meaning that they must be visualized with the use of an enhancement technique. Several factors influence the success rate of the detection of a fingermark. The sensitivity of the available methods to visualize fingermarks varies [16], meaning that not every technique has the same success rate. Furthermore, an incorrect choice of technique, an incorrect application of a technique or applying multiple techniques in the wrong order can result in lower success rates of finding a fingermark [17]. Another factor influencing the recovery probability is targeting of the correct location. Fingermarks could be missed by a wrong selection of locations to sample on the crime scene, resulting in a different probability to recover fingermarks. Other factors that impact on the probability of recovery are the level of background marks that are already present, and the criteria established to determine whether a fingermark is suitable for individualization.

For example, if partial fingermarks are present, these will most likely not be recovered if they are not of value for comparison. However, when the question is whether the suspect wore gloves, the presence of these partial fingermarks may very well influence the interpretation at activity level. As a result, the probability to recover fingermarks may vary between the activity level propositions at stake.

Combination of transfer, persistence and recovery

All three variables transfer, persistence and recovery influence the probability of the findings separately, but they cannot be clearly separated. If no fingermark is recovered, it does not automatically mean that the fingermark was not present (transfer). The fingermark could have been degraded such that visualization was not possible (persistence), the chosen enhancement technique could have been unsuccessful (recovery) or it may be the result of a combination of these factors. Therefore, these variables are often taken together and a single probability is assigned to the findings.

Background fingermarks

There are often already fingermarks present on items that are unrelated to the activities at stake. This means that the fingermarks could have already been present on the item before the alleged activity took place or may have ended up on the surface after the alleged activities took place. Fingermarks that are transferred to the surface by actions unrelated to the activities at stake are considered as background fingermarks. Consider, for example, that the issue is whether a suspect stabbed the victim with a knife or that an unknown person stabbed the victim with the knife. Say we find fingermarks of the suspect on the handle, as well as some fingermarks of one or more unknown individuals. Now the weight of the evidence given these two propositions would depend on the relation that the suspect has with the item (e.g. could he have handled the knife prior to or after the incident?), but also on the probability that we find background fingermarks on the handle of this specific knife. If the knife was cleaned recently, that probability may be low and the recovery of fingermarks of an unknown individual may support the suspect's proposition. However, if we have a high expectation of recovering background fingermarks (for instance because the knife is not a personal item and was in common use) the observed fingermarks of unknown individual(s) may be neutral towards the two propositions. The probability that these unknown fingermarks belong to background levels of fingermarks on the item should therefore be taken into consideration. During investigation, it is therefore important to consider the general activities that occurred prior to or after the alleged activities that may have resulted in fingermarks on the item.

2.2.2. Manner of deposition

Position of the hand and fingers during deposition

The way in which the fingermarks are deposited on a surface depends on the positioning of the hand and fingers during deposition. The position of the hand and fingers on an item may differ between activities, which is determined by the purpose of the activity, the anatomy of the human body and the physical characteristics of the item.

The anatomy of the human body causes restrictions in movements of the limbs. Due to these restrictions, the possible positions of the hand and fingers on an item are limited. The physical characteristics of the item also influence the position of the hand and fingers on an item. These

characteristics include size, weight, shape, structure, type of material, its function etc. Consider that someone grasps a knife for stabbing: he or she most likely grabs the knife at the handle due to the shape and structure of the knife. The physical characteristics of the handle of the knife influence the positioning of the hand and fingers, as may the purpose of the activity: cutting a piece of bread versus stabbing may for instance affect the way the knife is held.

Since the movements, the physical characteristics of the item and the goal of the activity may differ between activities, the position of the hand and fingers provides information that may assist in evaluating the findings given activity level propositions. Since it can be difficult to describe the position of the hand and fingers directly, we describe the position of the hand and fingers during deposition through four variables: location of the fingermarks, direction of the fingermarks, part of the hand that left the fingermark, and pressure.

Location of the fingermarks

The position of the hand and fingers on an item during deposition influences the location of the fingermarks on the item. De Ronde et al. [18] designed a model that can be used to analyse the location of fingermarks on 2–dimensional items given different activities. With the use of this model, pillowcases could be separated in the two activity classes smothering and changing, based on the location of the fingermarks on the pillowcases. This shows that the location of fingermarks on an item provides information on the activity that the donor carried out, and is therefore an important variable to take into account.

Direction of the fingermarks

When touching a surface, the hand and fingers are positioned in a certain direction. This direction varies between different activities and as such may be distinctive for particular activities. In the balcony case example, the fingermark direction as a result of climbing the balcony may be different from the fingermark direction as a result of leaning on the railing. The variable direction is used by crime scene officers to make inferences during the investigation phase on a crime scene. An example of this is that fingermarks found pointing inwards on the inside of a broken window frame are often considered to be related to the activity of climbing through a window during a burglary. However, there are no studies that report on the direction of fingermarks in relation to activities. The probability to find a certain fingermark direction under the different propositions may provide information on the activity level.

Area of friction ridge skin

Different activities require the use of different parts of the hand and therefore the area of friction ridge skin that left a fingermark may provide information on the activity. Consider the balcony case example: it may be more probable to recover a complete palm impression on the railing if the suspect climbed the balcony, than if the suspect simply touched the railing while standing on the balcony. The area of friction ridge skin that left the mark can be determined when the donor of the fingermark is known. In cases where a suspect or a corresponding reference print is absent, determining the area that left the print may be difficult.

Although recent research has focused on determining whether it was a left-hand or a right-hand that deposited an individual fingerprint [19–21], assigning a specific finger to a fingermark is still a topic for further research. Nevertheless, forensic examiners are trained to nominate corresponding fingers to fingermarks based on the size, pattern type, shape, etc. This information might be very valuable for the evaluation of fingermarks given activity level propositions. If a likelihood ratio can be determined on whether a recovered fingermark comes from a specific finger, or comes from another area of friction ridge skin, this information can be used in the evaluation of the findings.

Pressure

When friction ridge skin touches a surface, the shape of the skin changes as a result of the pressure applied on the surface and the pliability of the skin. Maceo [22] identifies two types of pressure of a finger on a surface: vertical pressure and horizontal pressure. An increased vertical pressure results in more points of contact with the surface, causing a broader fingermark [23]. Furthermore, vertical pressure affects the width of the ridges and the furrows in a fingermark [24]. As a result, the size of a fingermark and the width of the ridges in a fingermark may provide information about the vertical pressure applied. However, we expect that it will be very difficult to determine the vertical pressure applied to a surface by just looking at the fingermark, since the size of a fingermark, the width of the ridges and the condition of the skin varies greatly between donors.

Pressure in the horizontal plane causes deformation of the skin that may result in a distortion of the fingermarks in the form of smears or swipes [22]. This pressure distortion is often directional, and the distortion seldom moves in two directions [22, 24]. Studying these directional distortions in a fingermark can be of greater value for the interpretation at activity level. The probability of detecting a pressure distortion in a particular direction may be different for two activities and this information can be used in the assessment. Another possibility is that some activities may always result in distorted fingermarks. If the probability to obtain a distorted fingermark differs for two activities, this information may be of great value for the activity level interpretation.

2.3. Bayesian network construction

With the variables identified, we show the implementation of these in a Bayesian network. In this chapter, we focus on fingermark grips present on an item. By a grip, we refer to a collection of fingermarks for which it is assumed they are left in one and the same placement of the hand. This means the considered marks can vary from one fingermark to a complete hand mark, although they originate from one and the same hand and be deposited at the same time. In this chapter, we assume that the source of the fingermarks is identified or unknown. Recent literature on fingermarks at source level focus on a more probabilistic approach to present the evidential strength of a match [1, 25]. The implementation of this probabilistic source level information in Bayesian networks is considered outside the scope of this chapter; we refer the reader to Taroni et al. [4].

We built three different Bayesian networks, each based on a version of the balcony case example described in the introduction of this chapter. In the first case example, one grip is recovered on the railing and it is questioned whether the suspect climbed the balcony or leaned on the balcony. The second case example focuses on the question of whether the suspect climbed the balcony or someone else climbed the balcony. In the final case example, the implementation of multiple grips is discussed for the question whether the suspect climbed the balcony or someone else climbed the balcony. All three networks were built using the software Hugin (version 8.6)[2] and can be found in the supplementary material, Appendix A. For the purpose of illustration, we added some fictional probabilities in the network for the first case example. The probabilities used in this example are solely based on informed judgement of the authors, and are not based on any scientific experiments or published data.

Because the purpose of this chapter is to show the construction of Bayesian networks for the evaluation of fingermarks at activity level, we do not elaborate on how the variables can be objectively measured, nor do we aim to assign exact probabilities to the network. The main focus will be on the considerations a forensic scientist has to make when creating a Bayesian network to evaluate fingermarks given activity level propositions. In the discussion, we will elaborate on how probabilities can be assigned to the nodes and we propose topics for further research that will give substance to these probability estimations.

2.3.1. Case example 1: Nature of the activity disputed

Background information

Consider the balcony case example we described in the introduction. The police found a grip of fingermarks on the railing of the balcony, which leads to the assumption that the perpetrator entered the apartment via the balcony. The suspect, found through a database search, claims that his fingerprints are not left on the balcony due to an unauthorized intrusion via the balcony, but during a legal visit to the woman when leaning on the railing while smoking a cigarette. The dispute of the defense is aimed at the nature of the activity [26], resulting in the following activity level propositions:

H_p: *S climbed the balcony and did not lean on the railing.*
H_d: *S leaned on the railing and did not climb the balcony.*

Following the process described by Taylor et al. [27], we constructed the Bayesian network shown in Figure 2.1. The following sections describe the nodes, the dependencies and the considerations for the states of each node. We constructed this network to evaluate a positive result, e.g. a fingermark found on a surface. If no marks are recovered, the proposed Bayesian network would only consist of nodes (1) to (5), since determining the findings (6) to (12) is impossible.

Node (1) Propositions

The black node (1) *Propositions* in Figure 2.1 represents the main activity level propositions. This node has two states, H_p and H_d, representing respectively the proposition of the prosecution and the defense. Assignment of the prior probabilities is generally outside the domain of the forensic scientist. For the purpose of this example, we have assigned equal prior probabilities to each proposition (Table 2.1).

Propositions	Probability
H_p: S climbed the balcony and did not lean on the railing.	0.5
H_d: S leaned on the railing and did not climb the balcony.	0.5

Table 2.1: Prior probability table for the node (1) Propositions in Figure 2.1.

[2] https://www.hugin.com.

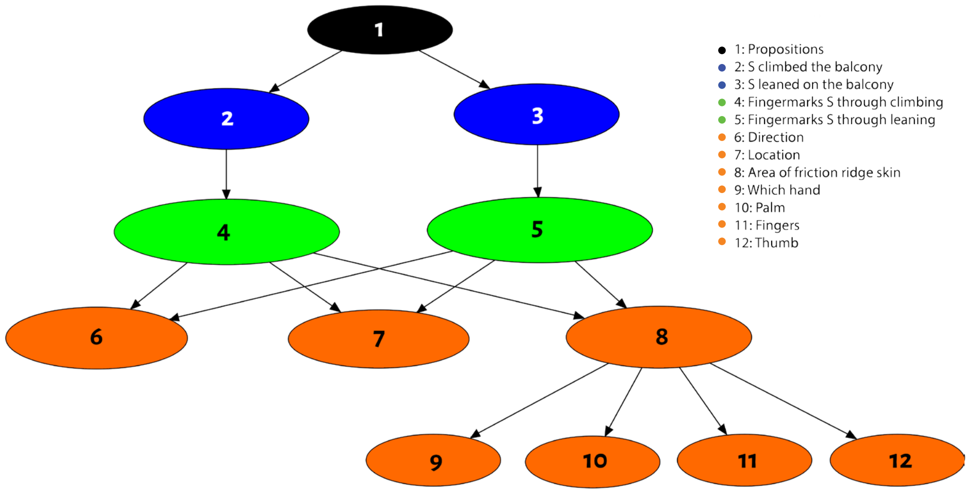

Figure 2.1: Bayesian network for the evaluation of fingermarks at activity level in case example 1.

Nodes (2) S climbed the balcony and (3) S leaned on the railing

The propositional node implies two activity nodes: (2) *S climbed the balcony* and (3) *S leaned on the railing*, denoted blue in Figure 2.1. We defined the states 'true' and 'false' to both nodes. The probabilities of the states of node (2) *S climbed the balcony* (Table 2.2) and node (3) *S leaned on the railing* (Table 2.3) are conditioned on the states of node (1) *propositions*. Table 2.2 shows that given that H_p is true, the node (2) *S climbed balcony* is true with probability $p = 1$ and false with probability $p = 0$. If H_d is true, the node (2) *S climbed the balcony* is true with probability $p = 0$ and false with probability $p = 1$. For the probability table of node (3) *S leaned on the railing* shown in Table 2.3, the reverse holds.

Propositions	H_p	H_d
S climbed the balcony:		
True	1	0
False	0	1

Table 2.2: Conditional probability table for the node (2) S climbed the balcony in Figure 2.1.

Propositions	H_p	H_d
S leaned on the railing:		
True	0	1
False	1	0

Table 2.3: Conditional probability table for the node (3) S leaned on the railing in Figure 2.1.

Nodes (4) Fingermarks S through climbing and (5) Fingermarks S through leaning

As a result of the activities climbing or leaning, fingermarks ended up on the railing. In Figure 2.1, the mechanisms by which the activities lead to the findings are represented by the green nodes (4) *Fingermarks S through climbing* and (5) *Fingermarks S through leaning*, both with states 'true' and 'false'. Within these nodes, the combined probabilities of transfer, persistence and recovery of the fingermarks as a result of the proposed activities are considered.

Table 2.4 shows the conditional probability table for the node (4) *Fingermarks S through climbing* . This node depends on the activity node (2) *S climbed the balcony* . Given that (2) *S climbed the balcony* is true, P_a denotes the probability to obtain fingermarks given the activity climbing. This incorporates the probabilities for transfer, the persistence and the recovery of fingermarks on the railing through climbing. From the fact that the states of nodes are mutually exclusive and exhaustive follows that the probability that there is no transfer, persistence and recovery of fingermarks through climbing is equal to $1 - P_a$. The probability table for the node (5) *Fingermarks S through leaning* is constructed in an equal manner.

S climbed the balcony	True	False
Fingermarks S through climbing:		
True	P_a	0
False	$1 - P_a$	1

Table 2.4: Conditional probability table for the node (4) Fingermarks S through climbing in Figure 2.1.

Node (6) Direction

One aspect we can observe from the recovered fingermarks is their direction. The node for this variable, node (6), is shown by the color orange in Figure 2.1. Before the direction of the fingermarks can be determined, the transfer, persistence and recovery of the fingermarks had to be successful, which means that node (6) *Direction* in the network is dependent on the probability to obtain fingermarks under the alleged activities. This is shown in Figure 2.1 by drawing an arrow from the nodes (4) *Fingermarks through climbing* and (5) *Fingermarks through leaning* to the node (6) *Direction*.

There are multiple options to define the states of the node (6) *Direction*; theoretically, every angle could be a separate state. In our case example, we chose to define two states for the direction of the fingermarks: the fingermarks are pointing inwards (to the house) and the fingermarks are pointing outwards (away from the house). The conditional probability table of the node (6) *Direction* is shown in Table 2.5. Assume that (4) *Fingermarks through climbing* is true and (5) *Fingermarks through leaning* is false, the probability to find inward pointing fingermarks is denoted by P_{c_1}.

Node (7) Location

Similar to node (6) *Direction*, node (7) *Location* is dependent on the nodes (4) *Fingermarks through climbing* and (5) *Fingermarks through leaning*, as shown by the arrows in Figure 2.1. In our case example, we assume that there is no direct dependency between the variable (7) *Location* and the variable (6) *Direction*. The probability to find the fingermarks on a particular location on the railing does not directly depend on whether the fingermarks are placed inwards or outwards and vice versa; they both directly depend on the activity that is carried out.

Fingermarks through climbing	True		False	
Fingermarks through leaning	True	False	True	False
Direction of the fingermarks:				
Inwards	*	P_{c_1}	P_{d_1}	*
Outwards	*	$1 - P_{c_1}$	$1 - P_{d_1}$	*

Table 2.5: Conditional probability table for the node (6) Direction in Figure 2.1. (*) denotes the fact that these probabilities represent situations which will not occur because the activities climbing and leaning are mutually exclusive in our example, and the network is not constructed to evaluate the absence of fingermarks.

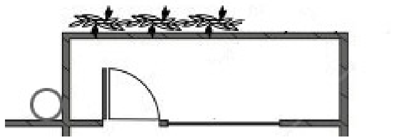

Figure 2.2: Top view of the balcony in scenario 1.

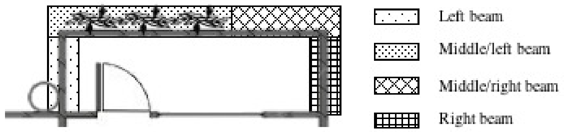

Figure 2.3: The four different areas representing the states of the node Location in Figure 2.1.

Figure 2.2 shows the top view of the balcony. During the investigation, it was determined that the only way to climb the balcony is via the drain pipe located on the left side of the balcony. For the states of the node (7) *Location*, we decided to divide the railing into four areas: the left beam, the middle/left beam (with planter), the middle/right beam and the right beam, as shown in Figure 2.3. Again, there are many ways to choose the possible states. For this scenario, we consider dividing the railing into these four areas appropriate given the structure and setup of the balcony. The left side is screened off by the door when open, the planter shields the railing and the four surface areas are approximately equal.

The probability table for the node (7) *Location* is shown in Table 2.6. Since there are four possible states, we denoted the probabilities of the states 'left', 'left/middle', 'right/middle' and 'right' in case (4) *Fingermarks through climbing* is true and (5) *Fingermarks through leaning* is false with P_{e_1}, P_{e_2}, P_{e_3} and $1-(P_{e_1}+P_{e_2}+P_{e_3})$. The probabilities in case (4) *Fingermarks through climbing* is false and(5) *Fingermarks through leaning* is true are denoted with P_{f_1}, P_{f_2}, P_{f_3} and $1-(P_{f_1}+P_{f_2}+P_{f_3})$.

Node (8) Area of friction ridge skin with sub-nodes (9) Which hand, (10) Palm, (11) Fingers and (12) Thumb

Given that it is known that the suspect left the fingermarks on the railing, the corresponding area of the hand that left the fingermarks can be determined. The node (8) *Area of friction ridge skin* with its sub-nodes (9) *Which hand*, (10) *Palm*, (11) *Fingers* and (12) *Thumb* are used to incorporate the variable area of friction ridge skin that left the fingermarks, as discussed in section 2.2.2.

Fingermarks through climbing	True		False	
Fingermarks through leaning	True	False	True	False
Location of the fingermarks:				
Left	*	P_{e_1}	P_{f_1}	*
Middle/left	*	P_{e_2}	P_{f_2}	*
Middle/right	*	P_{e_3}	P_{f_3}	*
Right	*	$1-(P_{e_1}+P_{e_2}+P_{e_3})$	$1-(P_{f_1}+P_{f_2}+P_{f_3})$	*

Table 2.6: Conditional probability table for the node (7) Location in Figure 2.1. (*) denotes the fact that these probabilities represent situations which will not occur because the activities climbing and leaning are mutually exclusive in our example, and the network is not constructed to evaluate the absence of fingermarks.

In our case example, we chose to divide the hand that left the fingermark(s) in three areas: the palm, the fingers and the thumb. Within the nodes (10) *Palm*, (11) *Fingers* and (12) *Thumb*, the part of the hand that left the marks can be specified. Each node has two possible states: 'true' and 'false'. Whether the marks came from the right or left hand can be specified within the node (9) *Which hand*, also with possible states 'true' and 'false'. All these nodes are connected to the summary node (8) *Area of friction ridge skin*, that combines all the information provided in the previous nodes. In this node, the probability of all possible combinations of the states of the nodes (9) *Which hand*, (10) *Palm*, (11) *Fingers* and (12) *Thumb* is summarized.

In some cases, differentiation between each finger or even between specific areas on the hand may be more appropriate since the probability of occurence of certain areas may differ bweteen the alleged activities. A direct result of defining smaller areas on the hand is that the number of states for the node (8) *Area of friction ridge skin* increases substantially, since each combination of the specified areas of each hand should be assigned a probability. For example, dividing the hand into six regions (five fingers and a palm) and accounting for the possibility that the left or the right hand is used, already results in 126 combinations. Assigning probabilities to all these separate combinations may become a difficult task. Since in our case example, we expected the probabilities to observe fingermarks of a specific finger to differentiate between climbing and leaning, we chose the three states 'palm', 'fingers' and 'thumb'.

Table 2.7 shows the probability table for the node (8) *Area of friction ridge skin*. From this table can be observed that a differentiation of three areas of the hand results in 14 possible states to which probabilities have to be assigned, varying from the probability to observe only the left-hand palm, to observing the combination of the right-hand's fingers, palm and thumb. We did not take into account combinations of the right and the left hand, since we limited our network to one grip of fingermarks for which is assumed the fingermarks are deposited by one hand.

2.3.2. Case example 2: Actor disputed

Background information

Consider the same scenario as described in case example 1, but instead of claiming that the climbing did not take place, the suspect claims that someone else must have climbed the balcony. He states that he visited the apartment a week earlier on invitation by the woman and smoked a cigarette on the balcony while leaning on the railing. The woman confirms the information that S visited a week earlier. The dispute of the defense is now aimed at the actor of the activity [26], resulting in the following activity level propositions:

Fingermarks through climbing	True		False	
Fingermarks through leaning	True	False	True	False
Area of friction ridge skin:				
Left - Palm	*	P_{g_1}	P_{h_1}	*
Left - Fingers	*	P_{g_2}	P_{h_2}	*
Left - Thumb	*	P_{g_3}	P_{h_3}	*
Left - Palm - Fingers	*	P_{g_4}	P_{h_4}	*
Left - Palm - Thumb	*	P_{g_5}	P_{h_5}	*
Left - Fingers - Thumb	*	P_{g_6}	P_{h_6}	*
Left - Palm - Fingers - Thumb	*	P_{g_7}	P_{h_7}	*
Right - Palm	*	P_{g_8}	P_{h_8}	*
Right - Fingers	*	P_{g_9}	P_{h_9}	*
Right - Thumb	*	$P_{g_{10}}$	$P_{h_{10}}$	*
Right - Palm - Fingers	*	$P_{g_{11}}$	$P_{h_{11}}$	*
Right - Palm - Thumb	*	$P_{g_{12}}$	$P_{h_{12}}$	*
Right - Fingers - Thumb	*	$P_{g_{13}}$	$P_{h_{13}}$	*
Right - Palm - Fingers - Thumb	*	$1-(P_{g_1}+\cdots+P_{g_{13}})$	$1-(P_{h_1}+\cdots+P_{h_{13}})$	*

Table 2.7: Conditional probability table for the node (8) Area of friction ridge skin in Figure 2.1. (*) denotes the fact that these probabilities represent situations which will not occur because the activities climbing and leaning are mutually exclusive in our example, and the network is not constructed to evaluate the absence of fingermarks.

H_p: *S climbed the balcony and S leaned on the railing.*
H_d: *U climbed the balcony and S leaned on the railing.*

The police still found only one grip of fingermarks. However, this situation is different from case example 1 since if the fingermark grip belongs to S, the probability that there are no fingermarks found of an unknown individual have to be taken into account. This results in the Bayesian network shown in Figure 2.4.

Nodes (2) U climbed the balcony, (3) S climbed the balcony and (4) S leaned on the railing
The propositions now imply three activities, which are defined with the nodes (2) *U climbed the balcony*, (3) *S climbed the balcony* and (4) *S leaned on the railing*, each with states 'true' and 'false'. Tables 2.8, 2.9 and 2.10 show the probability tables for these nodes. For example, in Table 2.8, given that H_p is true, the probability for the state 'true' of the node (2) *U climbed the balcony* is 0 and the probability for the state 'false' is 1.

Propositions	H_p	H_d
U climbed the balcony:		
True	0	1
False	1	0

Table 2.8: Conditional probability table for the node (2) U climbed the balcony in Figure 2.4.

Nodes (6) Fingermarks U through climbing, (7) Fingermarks S through climbing and (8) Fingermarks S through leaning
The three different activities each imply a different process by which fingermarks were deposited and persisted on the railing, represented by the nodes (6) *Fingermarks U through climbing*, (7) *Fingermarks S through climbing* and (8) *Fingermarks S through leaning*. These nodes have the states 'true' and 'false' and their probability tables are similar to the probability table for the node (4) *Fingermarks S through climbing* in case example 1, shown in Table 2.4.

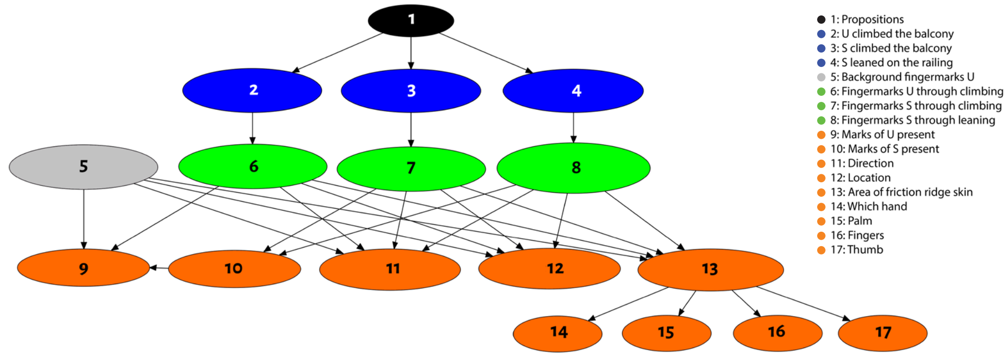

Figure 2.4: Bayesian network for the evaluation of fingermarks at activity level in case example 2.

Propositions	H_p	H_d
S climbed the balcony:		
True	1	0
False	0	1

Table 2.9: Conditional probability table for the node (3) S climbed the balcony in Figure 2.4.

Node (5) Background fingermarks U
In case example 2, there is another mechanism possible that needs to be considered: fingermarks of one or more unknown persons could already have been present prior to the activities that have taken place. This is denoted by the root node (5) *Background fingermarks U*, with states 'true' and 'false'. Within this node, we consider the probability of observing background fingermarks on the railing that are not a result of the disputed activities. In case no unknown fingermarks were found besides the fingermarks of S, the background node will be in state 'false' with a probability $p = 1$.

Nodes (9) Marks of U present and (10) Marks of S present
This section still focuses on one grip of fingermarks deposited during one hand placement. There are only two options for the source of the fingermarks: the fingermarks are from an unknown person U or the fingermarks are from S, denoted by the findings nodes (9) *Marks of U present* and (10) *Marks of S present*. Both nodes have states 'true' and 'false'. The arrow between these nodes represents the dependency between them: (10) if *Marks of S present* is true, (9) *Marks of U present* cannot be true.

The probability tables for the nodes (10) *Marks of S present* and (9) *Marks of U present* are shown in Tables 2.11 and 2.12. The node (10) *Marks of S present* depends on the two nodes (7) *Fingermarks S through climbing* and (8) *Fingermarks S through leaning*. Table 2.11 shows that if one of

Propositions	H_p	H_d
S leaned on the railing:		
True	1	1
False	0	0

Table 2.10: Conditional probability table for the node (4) S leaned on the railing in Figure 2.4.

these nodes is in state 'true', the probability that there are marks of S present is 1. If both of these nodes are in state 'false', there is a probability of 0 that there are marks of S present. The node (9) *Marks of U present* depends on three nodes: (6) *Fingermarks U through climbing*, (5) *Background fingermarks U* and (10) *Marks of S present*. Table 2.12 shows that if the node (10) *Marks of S present* is true, the probability that there are marks of U present is false. This is because we focus on one grip of fingermarks left during one placement.

Fingermarks S through climbing	True		False	
Fingermarks S through leaning	True	False	True	False
Marks of S present:				
True	1	1	1	0
False	0	0	0	1

Table 2.11: Conditional probability table for the node (10) Marks of S present in Figure 2.4.

Fingermarks U through climbing	True				False			
Background fingermarks U	True		False		True		False	
Marks of S present	True	False	True	False	True	False	True	False
Marks of U present								
True	*	*	*	1	*	1	0	0
False	*	*	*	0	*	0	1	1

Table 2.12: Conditional probability table for the node (9) Marks of U present in Figure 2.4.(*) denotes the fact that these probabilities represent situations which will not occur because the activities climbing and leaning are mutually exclusive in our example, and the network is not constructed to evaluate the absence of fingermarks.

Finding nodes (11) to (17)

The nodes (11) *Direction*, (12) *Location*, and (12) *Area of friction ridge skin* are defined the same way as described for case example 1, with an additional arrow from the nodes (5) *Background fingermarks U* and (6) *Fingermarks U through climbing*. The nodes (14) *Which hand*, (15) *Palm*, (16) *Fingers* and (17) *Thumb* are defined exactly the same way as described in section 2.3.1. An example of the probability table for the node (11) *Direction* in Figure 2.4 is shown in Table 2.13.

Background fingermarks U	True								False							
FM U through climbing	True				False				True				False			
FM S through climbing	True		False		True		False		True		False		True		False	
FM S through leaning	True	False	True	False	True	False	True	False	True	False	True	False	True	False	True	False
Direction:																
Inwards	*	*	*	*	*	*	*	P_{i_1}	*	*	*	P_{j_1}	*	P_{k_1}	P_{l_1}	*
Outwards	*	*	*	*	*	*	*	$1-P_{i_1}$	*	*	*	$1-P_{j_1}$	*	$1-P_{k_1}$	$1-P_{l_1}$	*

Table 2.13: Conditional probability table for the node (11) Direction in Figure 2.4.(*) denotes the fact that these probabilities represent situations which will not occur because the activities climbing and leaning are mutually exclusive in our example, and the network is not constructed to evaluate the absence of fingermarks.

2.3.3. Case example 3: Multiple grips

Background information

Often there is more than one grip of fingermarks found on an item. Suppose that in addition to the first grip, another grip is found on the railing. Again, the suspect claims that he visited the apartment a week earlier and leaned on the railing of the balcony and this information is again confirmed by the woman. The propositions brought forward by the prosecution and the defense are the same as used for case example 2:

H_p: *S climbed the balcony and S leaned on the railing.*
H_d: *U climbed the balcony and S leaned on the railing.*

Now the Bayesian network should account for two grips, resulting in the Bayesian network shown in Figure 2.5.

Structure of the network

The Bayesian network in Figure 2.5 consists of four modules. The network starts with a proposition node (1) *Propositions*, followed by the nodes describing the alleged activities: (2) *U climbed the balcony*, (3) *S climbed the balcony* and (4) *S leaned on the railing*. These nodes have the same setup as discussed for case example 2. Below these nodes are two nearly identical modules that represent two distinct fingermark grips. The first grip of fingermarks is described by the nodes on the left-hand side of the network, indicated by a (1). The second grip of fingermarks is described by the nodes indicated by a (2). Between these two sub-networks is a module consisting of four yellow nodes that describe dependencies between the two traces. We consider conditional dependencies between the two traces based on the location of the marks, the direction of the marks and whether or not the two marks were left by the same hand since the findings may be dependent on these factors. We consider them conditionally independent from the propositions. We chose these dependencies since we consider that the probability of the two marks being from the same donor is higher when they are found at the same location, have the same direction and are left by two different hands, than if either location or direction differ (where locations within reach of both arms still have an increased probability for the fingermarks being from the same source).

If the two grips are deposited during the same activity (holding the railing with both hands while climbing or leaning on the rail with both hands), there are two optional situations: the deposition of the two marks is strictly constrained in time, e.g. they must have been placed at the exact same moment during the same activity or the deposition of the two marks is less constrained in time and multiple interactions between hands and the railing took place during the same activity. To both situations, it applies that if the two fingermark grips are found in close proximity, this will influence the probability that they were left by the same individual, regardless of the activities defined in the propositions that led to their deposition.

If we assume the two marks are strictly constrained in time and were left through the same activity, given the case circumstances, there is a high probability that they will have the same direction, since it is unlikely to place one hand inwards and one hand outwards when carrying out the same activity in the same moment in time. Furthermore, if the two marks were left through the same activity at the same time, they cannot have been left by the same hand.

However, since both the activities leaning and climbing are a dynamic process, it is unlikely that this assumption holds. If multiple interactions between hands and railing may have taken

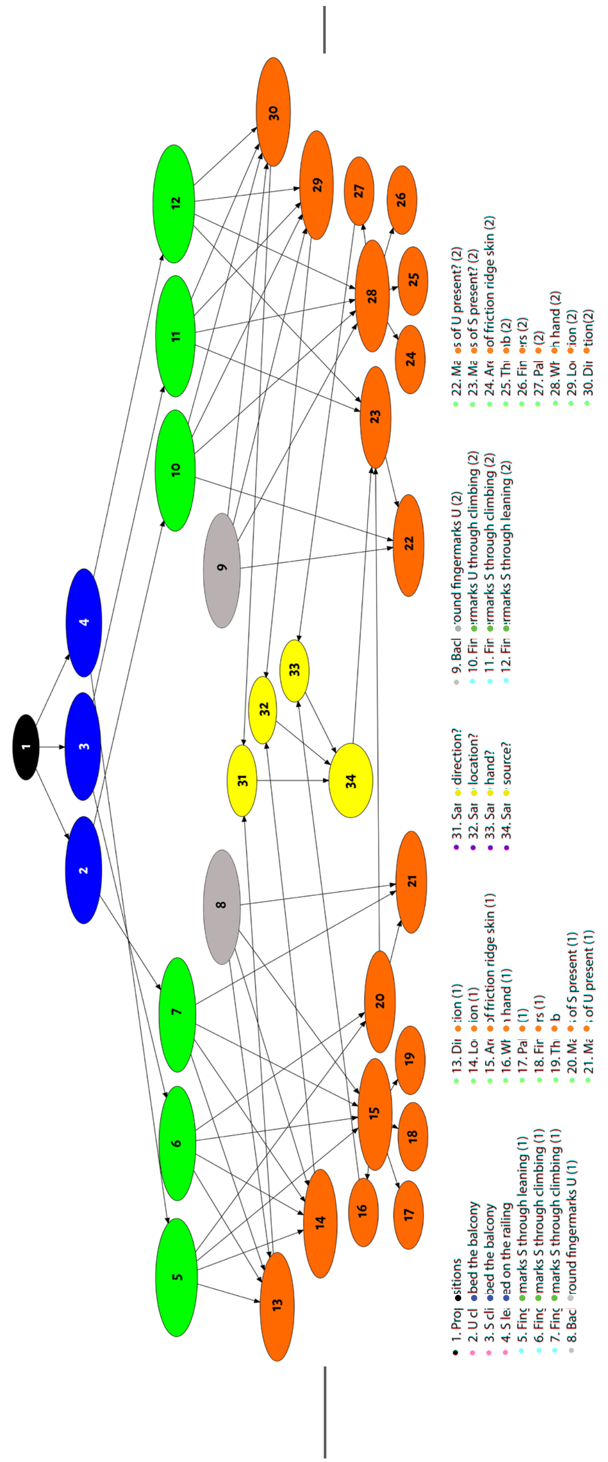

Figure 2.5: Bayesian network for the evaluation of two grips of fingermarks at activity level in case example 3.

place, it is not unlikely to find multiple marks of the same hand close together. Also, depending on how strict or broad the activities are defined in dynamics and time, it may be considered equally probable to find the marks having the same direction or a different direction. With a very broad definition and multiple interactions with the railing over extended periods of time, only location is expected to be a dependent factor between the two marks.

We have added four nodes to the network that model these dependencies. Node (31) *Same direction?* models whether both marks have the same direction or not (respectively state 'true' or 'false'), and is dependent of the direction nodes for the two separate grips. If the direction of both grips is equal, the node (31) *Same direction?* is in state true with a probability $p = 1$. Otherwise, the node (31) *Same direction?* is in state false with a probability $p = 1$. Node (32) *Same location?* models whether both marks have the same location. The states of this node consist of all possible combinations of the states for the nodes (14) *Location (1)* and (29) *Location (2)*, which results in ten combinations. If (14) *Location (1)* is left and (29) *Location (2)* is left, the node (32) *Same location?* is in state 'left-left' with a probability of $p = 1$. Choosing for two possible states 'true' and 'false' is also a possibility. However, in this case the proximity of two consecutive beams cannot be taken into account in node (34) *Same source*. The dependency between two hands is modelled within node (33) *Same hand?*, with states 'true' and 'false'. If (16) *Which hand (1)* and (28) *Which hand (2)* are both left, the node (33) *Same hand?* is true with a probability of $p = 1$. Node (34) *Same source?* contains a probability table that holds the probabilities for the fingermarks being from the same donor based on their respective locations, direction and left or right hand setting. Additionally, node (23) *Marks of S present (2)* is now dependent on node (34) *Same source?* and node (20) *Marks of S present (1)* (in addition to nodes (11) and (12)).

This network could be extended to a network that allows for the evaluation of more than two grips of fingermarks, by concatenating multiple sub-networks in the same way. When constructing such a network, possible new dependencies between variables describing different grips should be considered. A combined network accounting for multiple grips makes a complete analysis of all the fingermarks present on an item possible.

2.4. Discussion and conclusion

In this chapter, we have described a framework for the evaluation of fingermarks given activity level propositions with the use of Bayesian networks. We provided an overview of the current state of knowledge of the variables that provide information on fingermarks given activity level propositions, followed by an implementation of these variables in a Bayesian network using three case examples. The resulting networks enables the evaluation of (multiple) fingermark grips present on an item given propositions that dispute the activity that was carried out or given propositions that dispute the actor that carried out the activity.

The Bayesian networks proposed in this chapter could function as basic networks for the evaluation of fingermarks, with the possibility to be modified according to specific case circumstances. Furthermore, parts of the network may function as building blocks to create new networks for items other than a balcony railing, to evaluate fingermark grips given activity level propositions. Another advantage of using of Bayesian networks is that it makes the process of evaluation of the findings explicit. The network can be used as a tool to discuss the selected variables, the dependencies between them and the probabilities used, resulting in open discussions in court.

The principles discussed in this chapter are meant to be used as a guideline to help forensic scientists make well-considered choices depending on the case at hand. The proposed list of variables is a recommendation: it depends on the case circumstances which variables may be important to consider. The choice of the states of the variables also depends on the case circumstances, the possibilities to objectively measure the possible states and the feasibility of assigning probabilities to the states. These factors need to be carefully considered when selecting the states of the nodes. Similarly, we proposed dependencies between the variables based on our case example, which should be reconsidered when applying the framework to a different case example.

The final step to complete a Bayesian network is to assign probabilities to the nodes [28]. According to Taylor et al. [29], a forensic scientist has a number of options to do this (mentioned in order of preference): perform experiments by simulating the case circumstances, use values reported in literature from studies using similar case circumstances and outline the differences when reporting, consider a range of reasonable values and examine the sensitivity of the LR (see [30]), assign values based on the expert's experience or knowledge, or not carry out an evaluation. For fingermarks, the current situation is that evaluations of fingermarks given activity level are not carried out by forensic experts. This leaves the evaluation of fingermarks given activity level propositions up to the court although the forensic scientist has the specialized knowledge regarding the variables that is required to properly assign probabilities [29].

In the field of forensic biology, an increasing body of literature is available that aids in understanding the factors influencing transfer, persistence and recovery of DNA in relation to activities (see for example [31, 32]). These studies involve experiments in which participants carried out activities that resulted in touching surfaces or items, and factors like transfer and persistence were evaluated in relation to the activities performed. The study of fingermarks in time and space would benefit from similar experimental designs. Experiments into probabilities of transfer, persistence, recovery, direction, location of fingermarks, or what fingers are used when carrying out different activities with a particular item would help forensic scientists to assign probabilities to these variables in cases with similar case circumstances. Although the obtained probabilities may not always be directly applicable to other cases, the experimental data may still contribute to a scientific knowledge base [29] and may contribute to a better understanding of the general mechanisms of fingermark dynamics. Other recommendations for further research are designing methods to objectively measure a specific variable. For example, there is no method available to objectively measure the direction of a fingermark on a surface. Another example is the variable transfer: how do we measure the transfer of a fingermark to a surface as a result of an activity? Nowadays, fingermarks can be scored (for example by the CAST scale [14]) to compare the quality for individualization purposes. However, the quantity of fingermarks transferred to a surface may also provide information on activity level. These examples show that for some variables describing fingermarks at activity level, a clear definition or method to measure the variable is required before the variables can be described by case specific experiments.

With this study, we want to initiate the discussion about the evaluation of fingermarks given activity level propositions. Until now, this topic has barely been touched upon, possibly because the necessity is not acknowledged. However, an evaluation of fingermarks given source level propositions does not always amount to the activity [9]. In these cases, an evaluation of the fingermarks given activity level propositions could affect the strength of the evidence within the case circumstances. We hope this study will lead to new perspectives on this topic and stimulates opportunities for further research.

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3

Using case specific experiments to evaluate fingermarks on knives

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ABSTRACT

Bayesian networks have shown to be a useful tool for the evaluation of forensic findings given activity level propositions. In this chapter, we demonstrate how case specific experiments can be used to assign probabilities to the states of the nodes of a Bayesian network for the evaluation of fingermarks given activity level propositions. The transfer, persistence and recovery of fingermarks on knives is studied in experiments where a knife is either used to stab a victim or to cut food, representing the activities that were disputed in the case of the murder of Meredith Kercher. Two Bayesian networks are constructed, exploring the effect of different uses of the experimental data by assigning the probabilities based on the results of the experiments. The evaluation of the findings using the Bayesian networks demonstrates the potential for fingermarks in addressing activity level propositions.

3.1. Introduction

Evaluation of fingermarks given activity level propositions recently became a topic of interest [1, 2]. The question which activity led to the deposition of the fingermarks becomes relevant when the source of the fingermark is not in dispute. Research by de Ronde et al. [1] showed that there are multiple variables such as transfer, persistence, direction and pressure that may provide information when evaluating fingermarks given proposed activities that may have led to their deposition. One of these variables is the location of the fingermarks on an object. Based on an experiment with pillowcases, de Ronde et al. [2] have shown the value of the location of fingermarks with regards to assessing evidence for specific activities.

All variables that influence the interpretation of evidence given activity level propositions can be combined in a Bayesian network to evaluate evidence with regards to the relevant activities at stake [3]. A study by de Ronde et al. [1] has illustrated how Bayesian networks can be used for the evaluation of fingermarks given activity level propositions by presenting examples of Bayesian networks for a fictitious balcony case example. However, in that study, the assignment of probabilities to the conditional probability tables of the networks was left out of scope.

There are several sources of information that can be used to assign probabilities to the states of the nodes of a Bayesian network, mentioned in order of preference [4]. The forensic scientist may perform case specific experiments and base the probabilities implemented in the network on these empirical data. This option is preferred since these probabilities will align most closely with the circumstances of the case. Another possibility is to assign probabilities based on studies reported in literature that used experimental designs that are similar to the case circumstances. If no empirical data are available the probabilities could be informed based on expertise by the forensic scientist. This option, being subjective to a larger extent, is not preferred and puts a burden on the scientist to support their probability assignment. Sources for this could be a systematic review of resulting findings from similar cases, and/or expert elicitation from multiple experts. Whenever data are scarce or based on uncertain assumptions or sources, it is advisable to perform a sensitivity analysis to study the sensitivity of the likelihood ratio to reasonable variations in the assigned probabilities. If data are not available, or the sensitivity analysis determines the evaluation not to be robust, it may be decided that the findings from the evaluation will not be reported.

In this study, case specific experiments are carried out for a case example in order to show how this information can be used to evaluate fingermarks given activity level propositions. We will first present the case example and present two Bayesian networks that may be used for the evaluation of fingermarks found on a knife given case relevant activity level propositions. We describe the experiments that were performed and the data gained from those. We then demonstrate how the probabilities in the conditional probability tables of the Bayesian networks can be assigned based on the experimental data. Finally, we will show how the networks can be used to evaluate fingermarks given activity level propositions by calculating likelihood ratios for fictitious case findings.

3.1.1. Case example – The death of Meredith Kercher

On the morning of the 2nd November in 2007, Meredith Kercher was found dead on the floor of her bedroom. It appeared that she was stabbed in her neck and torso and it was established that these wounds were the cause of her death. Three suspects were identified: Rudy Guede, Kercher's flat mate Amanda Knox and Amanda's boyfriend Raffaele Sollecito. All three were convicted for the murder of Meredith Kercher. Amanda Knox and Rafaele Sollecito were later acquitted [5]. For this case example, we will focus on the claims that the prosecution and the defense made with regards to the knife that was submitted as evidence in the case against Knox and Sollecito.

There was no knife present on the crime scene, raising the suspicion that the murder weapon was removed. A knife was retrieved from a cutlery drawer in the apartment of Sollecito. The knife was tested for DNA, resulting in a matching DNA profile of Amanda Knox on the handle of the knife and a matching low-level DNA profile of Meredith Kercher on the blade of the knife. The knife was tested negative for the presence of blood [6]. The prosecution claimed that the knife was the murder weapon, however; the defense denied this statement and claimed that Knox used the knife for cooking in Sollecito's apartment.

3.1.2. Objectives

To the authors' knowledge, no fingermark examination was carried out on the knife and only DNA evidence present on the knife was used in this case. For this study, we investigate what kind of analysis could be performed when fingermarks were obtained from the knife in cases like this. In case fingermarks were found on the knife, the question in this case may shift from source level to activity level; the source of the fingermarks on the knife would not be disputed by the defense because the suspect provides an alternative explanation for the presence of her fingermarks on the knife, namely cooking with the knife. Therefore, the activity during which the marks were deposited is disputed and it would be of interest to evaluate the findings given the activity level propositions that may be put forward in this case.

3.2. Bayesian network construction

In this section, we discuss the process of constructing a Bayesian network to address the question whether the suspect Amanda Knox (S) used the knife to stab the victim Meredith Kercher (V) or used the knife to cut food while cooking. In this case, it is disputed whether the knife was the actual murder weapon and therefore we can formulate the following propositions, disputing the activity that is carried out:

H_p: *S stabbed V with the knife. S did not use the knife to cut food.*
H_d: *V was not stabbed with the knife. S only used the knife to cut food.*

All networks were built using the software Hugin (version 8.6)[1] and the corresponding .net files can be found in the supplementary material, Appendix B. For this study, several assumptions have been made:

1. We assumed that the collected evidence represents one fingermark grip on the knife, consisting of a collection of fingermarks for which is assumed that they are left in one and the same placement of the hand. This means that any handling of the knife prior to the alleged use (like taking if from a drawer or the dish washer) is disregarded.

[1] https://www.hugin.com.

2. The assumption is made that the source of the fingermarks is known to be the suspect and that no one else touched the knife.

3. The knife in the Kercher case is a 31 cm long knife with a 17.5 cm steel blade and a black, plasticized handle [7]. The knife we used in the experiments is a 22 cm long knife with a 11.5 cm steel blade and a black plasticized handle. We assume that the patterns of fingermarks on the knives resulting from the experiments are similar to those that would be obtained from a slightly larger knife.

4. We assume that the size of the hand of the suspect is an average human hand. The assigned probabilities are based on hands from volunteers ranging from small to large size hands.

5. We assume that the purpose of the grip on the knife handle is to use the knife as a tool. There are numerous ways to hold a knife. To use the knife as a tool for stabbing or cutting would make some of those ways improbable. For instance, it would be improbable that somebody would hold the knife with just a finger and a thumb on the handle to stab or cut. However, this is not impossible. Other ways may simply be impossible due to the intrinsic characteristics of both the knife and the hand, for example holding the knife with just a thumb. We assume that all the impossible, as well as the highly improbable ways to hold the knife are impossible in the context of the case. We will discuss this further in Section 3.4.

If an evaluation as discussed in this chapter would be applied to a real case, similar or other assumptions may need to be made [8]. The relevance of the assumptions may be discussed with the mandating authority together with the propositions being set prior to the evaluation being carried out. Also, the impact of such assumptions on the outcome of the evaluation can be addressed in the report.

3.2.1. Constructed Bayesian network

Based on the shape of a knife, it is expected that fingermarks may be observed on different locations of the knife when carrying out different activities. Three separate areas of the knife are therefore distinguished: the handle of the knife, the backside of (the handle of) the knife and the blade of the knife. Figure 3.1 shows the constructed Bayesian network, of which two versions (Bayesian network I and Bayesian network II) are presented below, both showing a different use of the experimental data by a different definition of the states of nodes 4 to 12. Bayesian network I focusses on evaluating the presence or absence of fingermarks on particular areas on the knife. Bayesian network II focusses on evaluating the area of friction ridge skin that was left on particular areas of the knive. The networks are created following the procedure described by de Ronde et al. [1], based on the template by Taylor et al. [9].

The presented network in Figure 3.1 has a structure that is different from the network for the evaluation of fingermarks given activity level propositions showed in figures 1, 4 and 5 presented by de Ronde et al. [1]. In that study, Bayesian networks were constructed for the evaluation of fingermark grips present on a balcony railing given the activity level propositions that the grip was a result of climbing the balcony or that the grip was a result of leaning on the railing. For the variable location in the balcony example, the balcony railing was divided into four different

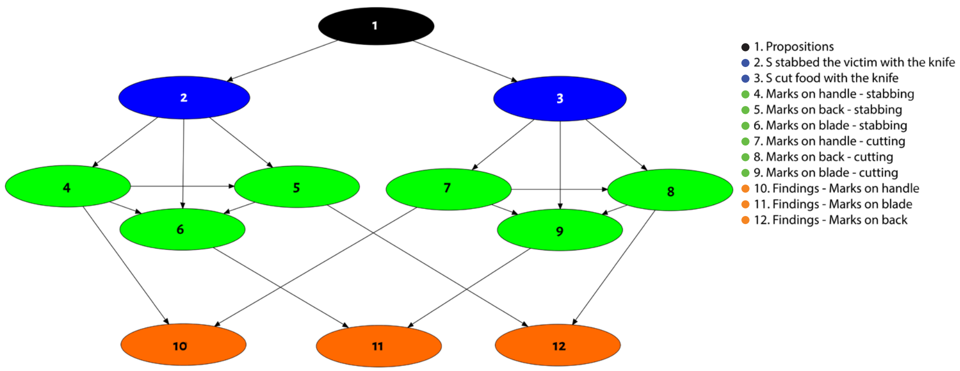

Figure 3.1: Bayesian network I and II, focusing on the different locations on the knife.

areas resulting into regions which were bigger than the size of a fingermark grip. As a consequence, fingermarks found in the regions were considered conditionally independent since the presence of a fingermark grip in one region was considered not to influence the probability for the presence of a fingermark grip in another region, given the assumption of a single deposition event that was made. For smaller items, such as a knife, a division of the item into regions may result into areas that are possibly smaller than the size of a fingermark grip and as such the presence of a mark on the handle of the knife may affect the probability of the presence of a mark on the backside or the blade of the knife. This causes conditional dependencies that should be taken into account, and therefore the nodes representing the transfer, persistence and recovery mechanisms have to be defined for each location region and activity separately. We suggest that for items for which the location is divided into regions that are of smaller size than a grip, additional dependencies have to be taken into account and the Bayesian network should be structured as described in sections 3.2.2 and 3.2.3.

3.2.2. Bayesian network I – Location of fingermarks on the knife

The first Bayesian network is constructed to evaluate the presence or absence of fingermarks on the knife.

Node (1) Propositions

Node (1)*Propositions* has two states, H_p and H_d, representing the propositions of prosecution and of defense respectively. We assigned an equal prior probability of $p = 0.5$ to both propositions, as shown in Table 3.1.

Propositions	Probability
H_p: S stabbed the victim with the knife. S did not use the knife to cut food.	0.5
H_d: V was not stabbed with the knife. S only used the knife to cut food.	0.5

Table 3.1: Prior probability table for the node (1) Propositions in Figure 2.1.

Nodes (2) S stabbed the victim with the knife and (3) S cut food with the knife

From the node (1) *Propositions*, two activities emerge: (2) *S stabbed the victim with the knife* and (3) *S cut food with the knife*, represented by the blue nodes in Figure 3.1. Both nodes have the states 'true' and 'false'. Table 3.2 and Table 3.3 show the probability tables for these nodes. Table 3.2 shows that if H_p is true, the node (2) *S stabbed the victim with the knife* is true with probability $p = 1$ and false with probability $p = 0$. If H_d is true, (2) *S stabbed the victim with the knife* is true with probability $p = 0$ and false with probability $p = 1$. Table 3.3 shows that for the node (3) *S cut food with the knife*, the reverse reasoning holds.

Propositions	H_p	H_d
S stabbed the victim with the knife:		
True	1	0
False	0	1

Table 3.2: Conditional probability table for the node (2) S stabbed the victim with the knife in Figure 3.1.

Propositions	H_p	H_d
S cut food with the knife:		
True	0	1
False	1	0

Table 3.3: Conditional probability table for the node (3) S cut food with the knife in Figure 3.1.

Nodes (4)(7) Marks on handle, (5)(8) Marks on back, (6)(9) marks on blade

Nodes (4),(5),(6),(7),(8) and (9) represent the combined probability of transfer, persistence and recovery of the fingermarks to a particular location of the knife as a consequence of the activity. This results in the nodes (4) *Marks on the handle - stabbing*, (5) *Marks on the back - stabbing* and (6) *Marks on the blade – stabbing* for the transfer, persistence and recovery of fingermarks to a particular location on the knife for the scenario stabbing and the nodes (7)*Marks on the handle - cutting*, (8)*Marks on the back - cutting* and (9)*Marks on the blade – cutting* for the transfer, persistence and recovery of fingermarks to a particular location on the knife for the scenario cutting food. These nodes each have two states: 'fingermarks S present' and 'fingermarks S absent'. The conditional dependencies between the three locations should be considered. These dependencies are modelled in the Bayesian network by adding an arrow from node (4)*Marks on the handle – stabbing* to node (5)*Marks on the back – stabbing*, and arrows from nodes (4) and (5) to node (6) *Marks on the blade – stabbing*. The same connection has been made between nodes (7).(8) and (9), as shown in Figure 3.1. The probabilities assigned to the conditional probability tables in these nodes are based on the conducted knife experiment, and will be discussed in Section 3.4.

Nodes (10) Findings – Marks on handle, (11) Findings – Marks on blade and (12) Findings – Marks on back

Node 10 *Findings – Marks on handle* in Figure 3.1 is a summary node, representing the presence or absence of fingermarks on the handle of the knife, with the two possible states 'fingermarks S present' and 'fingermarks S absent'. Given the propositions and assumptions that were made, we do not consider marks by other individuals. The nodes (11) *Findings – Marks on blade* and (12) *Findings – Marks on back* are similarly defined and represent respectively the presence or absence of fingermarks on the blade of the knife and on the backside of the handle of the knife. Table 3.4 shows the conditional probability table for node (10) *Findings – Marks on handle*. If either (4)*Marks* *on handle - stabbing* or (7)*Marks on handle - cutting* are in state 'fingermarks S present', the node (10)*Findings – Marks on handle* is in state 'fingermarks S present' with probability $p = 1$ and in state 'fingermarks S absent' with probability $p = 0$. The conditional probability tables for nodes (11) *Findings – Marks on blade* and (12) *Findings – Marks on back* are similarly defined.

Marks on handle - stabbing	FM S present		FM S absent	
Marks on handle - cutting	FM S present	FM S absent	FM S present	FM S absent
Findings – Marks on handle:				
True	1*	1	1	0
False	0*	0	0	1

Table 3.4: Conditional probability table for the node (10) Findings – Marks on handle in Figure 3.1. (*) denotes the fact that these probabilities represent situations which will not occur because the activities stabbing and cutting food are both mutually exclusive (within the context of the example case).

3.2.3. Bayesian network II – area of friction ridge skin on the knife

Thus far, we have dealt with the findings on the knife as presence or absence of fingermarks only. It is up to the scientist to decide which level of detail in the findings will be considered in their evaluation. The choice will often be dictated by the observations made in the case (can certain details be determined?), available data on transfer, persistence and recovery (do the data provide sufficient detail to assign probabilities?), and the contextual information in the case (does the question that needs answering require a certain level of detail?) [10].

From the knife experiment, we observed that a considerable difference between the two activities stabbing and cutting food was shown in observing particular areas of friction ridge skin on particular locations on the knife. We decided to add this information to network II. The hand that left the fingermarks is divided into three areas of friction ridge skin: the palm, the fingers and the thumb. To each transfer, persistence, and recovery node representing the handle, the backside and the blade of the knife, as well as the three findings nodes, we defined the states based on all possible combinations of the three areas of friction ridge skin, leading to the seven states: 'palm', 'fingers', 'thumb', 'palm/fingers', 'palm/thumb', 'fingers/thumb', 'palm/fingers/thumb' and 'none'. An extra state 'undetermined' is added to each of these nodes representing fingermarks for which it is impossible to determine what area of the hand left the mark.

When combining the variables location and area of friction ridge skin, additional conditional dependencies between these variables should be considered. For example, if a thumb mark is observed on the backside of the knife, this will influence the probability of observing particular areas of friction ridge skin on the handle and the blade of the knife, due to the shape of the knife and the shape of a hand. Since this dependency exists regardless of the activity that is carried out, these variables are considered to be conditionally dependent of each other and should be modelled in the Bayesian network by adding an arrow between them [3]. This results in a Bayesian network that is similarly structured as Bayesian network I but with the states of nodes (4) to (12) defined to include the area of friction ridge skin (thumb, palm, and fingers).

3.3. Knife experiment

3.3.1. Experimental protocol

A within-subjects design was used in which each participant conducted the same experimental tasks. Before the start of the experiment, informed consent was obtained from all participants, with which the participants gave permission for the use of their fingermarks for research purposes. A total of 24 students of the Amsterdam University of Applied Sciences (7 males, 17 females, all right-handed donors) carried out two separate scenarios, each with the use of a different knife. In the first scenario, each participant was asked to pick up a knife from the table and to stab three times into a Styrofoam plate on which a silhouette of a person was drawn (Figure 3.2). The fingermarks on the knives were directly visualized using cyanoacrylate fuming. In the second scenario, each participant was asked to pick up a knife from a table and to cut a piece of gingerbread into four pieces (Figure 3.2), representing the activity cutting food with a knife. Again, the fingermarks on the knives were directly visualized using cyanoacrylate fuming.

The type of material that is being cut may affect the handling of the knife. Different structure or texture, or hardness of the material may affect the amount of force being used (hence impact on the pressure asserted by the individual performing the cutting as well as on the friction between hand and knife resulting from this) as well as the positioning of the hand. Further work is needed to explore the impact of these and other variables on the probability of transfer, persistence, and recovery of marks from friction ridge skin on surfaces. This, however, is outside the scope of the current study.

In this experiment, natural fingermark samples were used, collected with minimal interference from the researchers to represent the conditions of the case as closely as possible and variables such as duration, pressure, temperature and time between washing hands were not controlled. Between the two scenarios, a week time span was taken. The participants were not provided with instructions on how to handle the knife when carrying out the activities.

3.3.2. Materials

For the knives, steak knives of the model SNITTA purchased at IKEA were used (Figure 3.2). These are 22 cm long knives with a 11.5 cm blade and a plastic coated black handle. The knives were cleaned with the use of acetone, followed by cleaning with ethanol (70%), rinsing with demi water and drying using Tork paper. For the stabbing scenarios, a Styrofoam plate was placed on a wooden stand and covered with plastic, on which a silhouette of a person with the height of 1.78 m was drawn, as shown in Figure 3.2. After each stabbing scenario was carried out, the plastic was replaced to prevent a bias for the next participant of where to stab. After the stabbing the knives were put on a table and not covered or packaged. The fingermarks were directly visualized using cyanoacrylate fuming (1,5 g, 120 C) in a MVC3000 fuming system (Foster and Freeman LTD) at 80% humidity. Afterwards, the knives were directly photographed using a Nikon D60. All experiments were filmed using a Logitech C615 HD webcam.

3.3.3. Analysis

During the experiment, two knives were collected for each donor. After visualization, the knives were photographed by taking four pictures of each side of the knife. For the analysis, pictures of the knives and the video footage of the scenarios were scored by a single researcher using a pre-

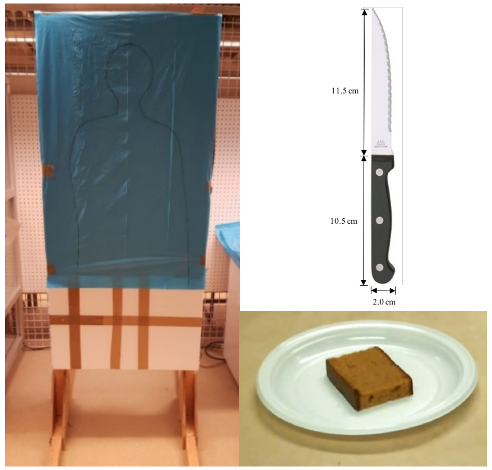

Figure 3.2: Stabbing construction (left), steak knife used in the experiments (right, up) and gingerbread used for the cutting scenario (right, down).

defined set of variables. During this analysis, the final grip that was used for the activity of stabbing or cutting food was scored. The researcher scored whether fingermarks were visualized (yes/no), which hand they used (left/right), the direction of the knife (overhand/underhand), the rotation of the knife (cutting face of the knife pointing upwards or downwards) and what area of friction ridge skin on the hands were left on which location on the knife. For coding the location and the area of friction ridge skin, the knife was divided into 6 regions: side 1, the topside of the knife handle (S1); side 2, rotating the knife 90 degrees from the topside to the right side of the knife handle (S2); side 3, the downside of the knife handle (S3); side 4, rotating the knife 90 degrees from the downside to the left side of the knife handle (S4); the backside of the knife (back) and the blade of the knife (blade). Regions S1-S4 on the knife handle are shown in Figure 3.3.

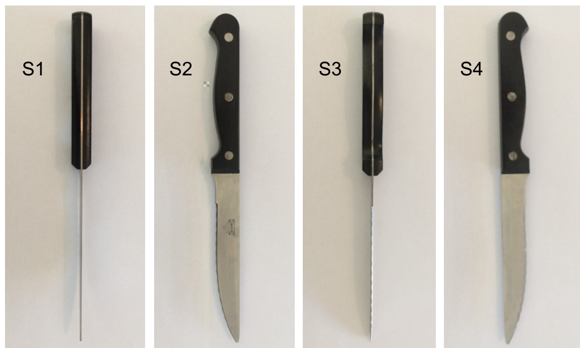

Figure 3.3: Division of the knife handle into areas S1, S2, S3 and S4.

For each location on the knife was denoted what area of friction ridge skin was observed in the video footage: palm, fingers, thumb and all combinations thereof. If the area was not touched, the score 'none' was given. For the scoring procedure, the grip used during the activity observed from the video footages, was compared to the pictures of the visualized fingermarks on the knives to determine what area of the hand left the marks present on the knife. The focus of this scoring was not on the quality of the fingermarks, therefore not only identifiable fingermarks were scored but also fingermarks that would possibly not be suitable for identification such as smears or lower scoring fingermarks [11]. To fingermarks for which it was difficult to determine what area of the hand left the mark, a score of NA was assigned.

All video footages, pictures and the corresponding scores were double checked by the researcher that scored the files. The videos that were in some respect unclear due to for example movement of the camera were discussed with an additional researcher. In case of agreement, the area of friction ridge skin was assigned, otherwise a score of NA was assigned. This process showed that the coding procedure was a straightforward process with a high degree of intra- and intercoder reliability.

3.3.4. Results

Table B.1 and Table B.2 in supplementary material, Appendix B show the observations for the experiment in which the participants used the knife for stabbing and for the experiment in which the participants used the knife to cut food, respectively. These tables show that for each scenario and for each donor, fingermarks were visualized on the knife (column FM = yes).

The video footages showed that there were two optional directions for the grip as a result of holding the knife. The first is to hold the knife in an 'overhand' position such that the wrist is located higher than the elbow and the knife is carried at shoulder height or higher, resulting in a grip in which the thumb is placed near the backside of the knife handle. The second option is to hold the knife in an 'underhand' position such that the wrist is located lower or at equal height as the elbow and the knife is held at stomach height or lower, resulting in a grip in which the thumb is located near the blade side of the knife handle. Table B.1 shows that 54% of the donors that carried out the stabbing scenario held the knife in the overhand position. Table B.2 shows that the overhand grip was not observed for the cutting food scenario. This seems logical in view of the activity; cutting food with the knife in an overhand position can be considered rather uncomfortable. The results confirm our expectation that the direction of the grip on the knife can be distinctive between the activities stabbing and cutting food.

During the experiment, we observed that two participants rotated the knife during the scenario of stabbing such that the cutting face of the knife pointed upwards (Table B.1). This rotation was not observed for the scenario of cutting food (Table B.2), due to the fact that it is impossible to cut food with the cutting face of the knife upwards. Therefore, the rotation of the knife can also be considered as a distinctive feature between the activities stabbing and cutting food.

Important to note is that the variables 'direction' and 'rotation' of the knife as described here cannot be directly observed in casework and video footages were used in this experiment to observe these features. However, the variables location on the knife and the area of friction ridge skin observed on a specific location indirectly provide information on the direction and the rotation in which the knife was held. For this reason, only the results for the presence of the fingermarks, the area of friction ridge skin and the location on the knife in Table B.1 and Table B.2 in Appendix B were used to assign probabilities to the states of the nodes of the Bayesian networks.

3

3.4. Probability assignments and evaluations using the Bayesian networks

For the probability assignments to the states of the nodes of the Bayesian networks, the probability for state i of node k with $n_{i,k}$ observations can be defined as:

$$P_{i,k} = \frac{n_{i,k}+1}{I+\sum_{i=1}^{I} n_{i,k}} \tag{3.1}$$

where I represents the number of different states for node k [9,12]. NA observations were considered as 'fingermarks present' when assigning probabilities to the states of the TPR nodes of network I, and as 'undetermined' when assigning probabilities to the states of these nodes in network II. We have assumed that each (technically possible) way of holding the knife is equally probable, and as a consequence consider each distribution of friction ridge skin marks on the knife equally probable (a priori). We have therefore assigned the same prior counts to each defined state.

However, some combinations of locations and area of friction ridge skin are impossible to realize in one grip due to the assumptions of our study, the shape of the knife or the restrictions in the movements of the hand. For example, a single thumb cannot be placed on the handle, the backside and the blade of the knife since only single grips are evaluated in this study. We decided to assign a probability of zero to these impossible combinations, denoted by the color gray in the conditional probability tables for the nodes.

To the authors' knowledge, the knife in the case of the murder of Meredith Kercher was not examined for fingermarks. Therefore, when evaluating findings using the three Bayesian networks, we will consider several fictitious findings that could be obtained in a case like this and we will calculate the weight of the evidence. We note that the values which we calculate with the Bayesian networks in this section, are effectively posterior probabilities. Since we have only two propositions in the proposition nodes, and their assigned prior probabilities are equal, the ratio of the posterior probabilities equals the likelihood ratio. Hence, we refer to the ratio of the posterior probabilities as likelihood ratios (LR) from here on.

3.4.1. Bayesian network I – location of fingermarks on the knife

Table 3.5 and Table 3.6 show the conditional probability tables for the nodes (4) *Marks on handle – stabbing* and (7) *Marks on handle – cutting* in Bayesian network I with states 'fingermarks S present' and 'fingermarks S absent', in which the probabilities are assigned based on the experimental results shown in Table B.1 and Table B.2 in Appendix B. The tables show that observing fingermarks on the knife handle does not provide any information on the activity that is carried out, since the probability to observe fingermarks on the knife handle is equal given the two propositions stabbing and cutting food.

S stabbed the victim with the knife	True	False
Marks on handle - stabbing:		
Fingermarks S present	0.96	0
Fingermarks S absent	0.04	1

Table 3.5: Conditional probability table for the node (4) Marks on handle - stabbing in network I.

S cut food with the knife	True	False
Marks on handle - cutting:		
Fingermarks S present	0.96	0
Fingermarks S absent	0.04	1

Table 3.6: Conditional probability table for the node (7) Marks on handle - cutting in network I.

3

Table 3.7 and Table 3.8 show the conditional probability tables for the nodes (5) *Marks on back – stabbing* and (8) *Marks on back – cutting* in network I, respectively. The results show that the probability that fingermarks are present on the backside given that S stabbed the victim with the knife and marks were observed on the handle is considerably lower than the probability that fingermarks are present on the backside given that S cut food with the knife and marks were observed on the handle.

S stabbed the victim	True		False	
Marks on handle - stabbing	FM S present	FM S absent	FM S present	FM S absent
Marks on back - stabbing:				
Fingermarks S present	0.62	0.5	0	0
Fingermarks S absent	0.38	0.5	1	1

Table 3.7: Conditional probability table for the node (5) Marks on back – stabbing in network I.

S cut food with the knife	True		False	
Marks on handle - cutting	FM S present	FM S absent	FM S present	FM S absent
Marks on back - cutting:				
Fingermarks S present	0.92	0.5	0	0
Fingermarks S absent	0.08	0.5	1	1

Table 3.8: Conditional probability table for the node (8) Marks on back – cutting in network I.

The conditional probability tables for the nodes (6) *Marks on blade – stabbing* and (9) *Marks on blade – cutting* are shown in Table B.3 and Table B.4 in supplementary material, Appendix B. These results show that the probability to observe fingermarks on the blade given that the fingermarks ended up on the knife through stabbing is very low and for almost all participants, fingermarks were absent on the blade. On the contrary, the probability to observe fingermarks on the blade given that the fingermarks ended up on the knife through preparing food are almost equal if marks are also observed on the handle and the backside of the knife. If marks are only observed on the handle, the probability to observe fingermarks on the blade of the knife is slightly higher than to not observe fingermarks on the blade.

3.4.2. Bayesian network I – exploration

Instantiating propositions H_p and H_d consecutively in network I (link to the Hugin files can be found in the supplementary material, Appendix B) shows that the probability for the presence or absence of fingermarks on the knife handle is equal given both propositions, showing that the presence or absence of fingermarks on the knife handle indeed does not provide any evidential value. When evaluating the findings that fingermarks of S are present on all three areas of the knife, the findings support the proposition that the suspect cut food with the knife. If the fingermarks of S are only present on the knife handle and not on the backside and the blade of the knife, the findings support the proposition that the suspect stabbed the victim with the knife. In case we evaluate the absence of fingermarks on the knife, the findings do not add any evidential weight and result in an LR of 1. This can be explained by the fact that this finding was not observed in our experiment.

3.4.3. Bayesian network II – area of friction ridge skin on the knife

3

Table 3.9 shows the conditional probability table for the node (4) *Marks on handle – stabbing* and Table 3.10 shows the conditional probability table for the node (7) *Marks on handle - cutting* in Bayesian network II. The probabilities are assigned based on the experimental results shown in Table B.1 and Table B.2 in Appendix B, for which the observations in columns Side 1, Side 2, Side 3 and Side 4 are combined to represent the findings on the handle. The results show that for both propositions, the probability to observe the palm, the fingers and the thumb on the handle is the highest. Therefore, the area of friction ridge skin observed on the knife handle provides only little information on the activity that is carried out.

For the nodes (4) *Marks on handle – stabbing* and (7) *Marks on handle – cutting* is determined that the state 'thumb' is considered impossible to achieve due to the fact that placing only the thumb on the handle without the palm or fingers makes it impossible to even carry the knife. This state is therefore removed from the tables.

S stabbed the victim with the knife	True	False
Marks on handle - stabbing:		
Palm	0.031	0
Fingers	0.031	0
Palm/Fingers	0.156	0
Palm/Thumb	0.031	0
Fingers/Thumb	0.031	0
Palm/Fingers/Thumb	0.625	0
Undetermined	0.063	0
None	0.031	1

Table 3.9: Conditional probability table for the node (4) Marks on handle – stabbing in network II.

S cut food with the knife	True	False
Marks on handle - cutting:		
Palm	0.031	0
Fingers	0.031	0
Palm/Fingers	0.063	0
Palm/Thumb	0.031	0
Fingers/Thumb	0.031	0
Palm/Fingers/Thumb	0.75	0
Undetermined	0.063	0
None	0.031	1

Table 3.10: Conditional probability table for the node (7) Marks on handle – cutting in network II.

The conditional probability tables for the nodes (5) *Marks on back – stabbing* and (8) *Marks on back – cutting* can be found in the supplementary material, Appendix B. Since these nodes are conditionally dependent on the marks observed on the handle, there are again multiple combinations of locations and area of friction ridge skin which are considered impossible given the alleged activities and therefore received a probability of zero (denoted gray in the conditional probability tables).

The conditional probability tables for the nodes (6) *Marks on blade – stabbing* and (9) *Marks on blade – cutting* can also be found in Appendix B. Since these nodes are conditionally dependent on the nodes (4)(7) *Marks on handle* and (5)(8) *Marks on backside*, the location combinations which were already considered impossible for these nodes are removed from the conditional probability table. New combinations which can be considered impossible to achieve with the disputed knife and a human hand are again marked with gray cells and receive a probability of zero.

3

3.4.4. Bayesian network II – exploration

The experimental results showed that thumbs were only placed on the backside of the knife in case the knife was held in an overhand grip, which only occurred for the scenario in which participants stabbed using the knife. Therefore, we are interested in the evidential value provided by the model for this observation. There are four states for the node (12) *Findings – Marks on back* that incorporate the presence of a thumb on the backside of the knife: the states 'thumb', 'palm/thumb', 'fingers/thumb' and 'palm/fingers/thumb'. Instantiating one of these states for the node (12) *Findings – Marks on back* provides a LR in support for the proposition that the suspect stabbed the victim with the knife.

The results from the experiment showed that 13 participants placed their fingers on the blade of the knife while cutting food, whereas for the stabbing scenario, this was only one participant. When evaluating the finding that fingers were observed on the blade, the findings support the proposition that the suspect cut food with the knife.

The network also shows that in case no fingermarks are found on the handle of the knife, the only possibility to hold the knife is to hold the knife at the blade with the palm/fingers, palm/thumb, fingers/thumb or the palm/fingers/thumb. Additionally, when no fingermarks are found on the handle of the knife, the only possible finding for the back of the knife is that no fingermarks are observed, since it is considered impossible to hold the knife while only touching the back of the knife and not the handle of the knife.

3.4.5. Evaluating fictitious findings in the Meredith Kercher case

In this section, we would like to explore the use of the constructed Bayesian networks to evaluate possible findings in the Mereditch Kercher case. To the authors knowledge, no fingermark examination was carried out on the knife in the Meredith Kercher case, causing the evaluations carried out in this section to be solely based on fictitious findings.

Suppose that the knife that was retrieved from the apartment of Sollecito contained marks of the fingers, the palm and the thumb on the handle, marks of the fingers on the blade of the knife and marks of the palm and the fingers on the backside of the knife. When evaluating these findings using network I, the state 'present' is instantiated for the nodes (10) *Findings – Marks on the handle*, (11) *Findings – Marks on the blade* and (12) *Findings – Marks on the back*, shown by the red bars for these nodes in Figure 3.4. This results in a LR of 7 in support of the proposition that the suspect used the knife to cut food. When evaluating these findings using network II, the state 'palm/fingers/thumb' is instantiated for node (10) *Findings – Marks on the handle*, the state 'fingers' is instantiated for node (11) *Findings – Marks on the blade* and the state 'palm/fingers' is instantiated for the node (12) *Findings – Marks on the back*, resulting in a LR of 34 in favor of Hd. This means that under the propositions stated and the assumptions mentioned in Section 3.2, the findings are 34 times more probable if the suspect cut food with the knife than than if the suspect used the knife for stabbing.

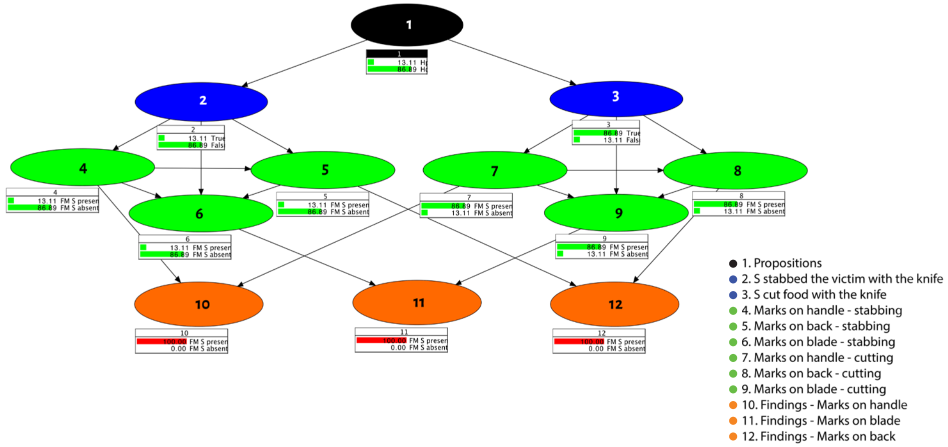

Figure 3.4: Bayesian network I or which the findings fingermarks present on the handle, fingermarks present on the blade and fingermarks present on the backside are instantiated.

Now consider that the following fingermarks were retrieved from the knife: marks of the fingers and the palm on the handle, no fingermarks on the blade of the knife and a mark of the thumb on the backside of the knife. When evaluating these findings using network I, the state 'present' is instantiated for the nodes (10) *Findings – Marks on the handle* and (12) *Findings – Marks on the back* and the state 'absent' is instantiated for the node (11) *Findings – Marks on the blade*. The resulting LR is 1 demonstrating that with network I the findings are equally probable given both propositions. When evaluating these findings using network II, we obtain a LR of 35 in support of Hp, as shown in Figure 3.5.

One requirement for a formal probabilistic assessment given activity level propositions is that the outcome of the evaluation is robust [13]. To test this, a sensitivity analysis can be performed to assess the impact of reasonable variations in the assigned probabilities on the resulting LR. We refrain from doing so with these fictitious findings in the Meredith Kercher case. For an example of the use of sensitivity analyses we refer the interested reader to Szkuta et al. [14].

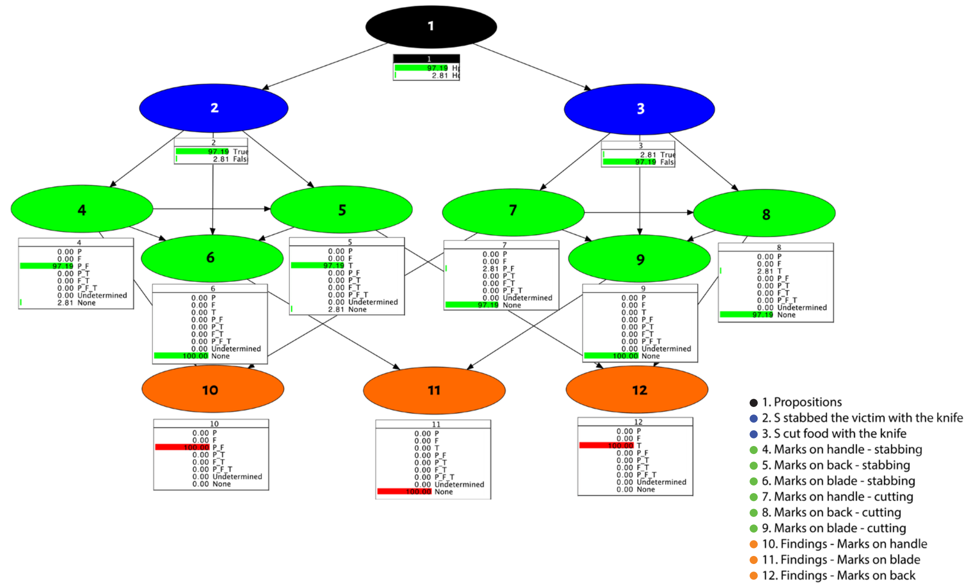

Figure 3.5: Bayesian network II for which the findings palm and fingers on the handle, no fingermarks on the blade and thumb on backside are instantiated.

3.5. Discussion

The purpose of this study was to demonstrate how data resulting from case specific experiments can be used to assign probabilities to the states of the nodes of a Bayesian network for the evaluation of fingermarks given activity level propositions. For this purpose, we conducted an experiment in which a knife was either used to stab a victim or to cut food, representing the activities that were disputed in the case of the murder of Meredith Kercher. Two Bayesian networks were constructed: one to evaluate the presence or absence of fingermarks on particular locations of the knife and one to evaluate the area of friction ridge skin that was left on particular locations of the knife. Probabilities were assigned based on the empirical data resulting from the knife experiment and we explored the LR calculated with the models.

We would like to emphasize that the Bayesian networks are a result of many choices made during the process. For example, the choice of how to divide the knife into different locations or how to divide the hand into different areas directly influences the construction of the network. This is often a tradeoff between obtaining as much information as possible from the experimental data versus the amount and quality of the data that are available to inform the probability assignments. For example, based on the collected data for the knife experiment, it could be questioned whether a further division of the knife handle into four separate areas would provide more information. However, when defining more states to a node, the number of observations for each state will decrease when using the same sample size for the experiment. The conditional probability tables for network II already showed that dividing the knife into three areas caused many states for which no observations were available. Increasing the number of location nodes while assigning the probabilities based on the same sample size will cause the LR to be less informative (e.g. approaching 1). Therefore, the design of the network always depends on data available to inform the probability assignments.

In this study, we did not focus on the quality of the fingermarks with regards to source level information, a measure that is nowadays used to select the fingermarks that are collected from a crime scene [15]. For cases in which the donor of the fingermarks remains unknown, network I focusing on the presence or absence of fingermarks on the knives can very well be used to evaluate the fingermarks given activity level propositions since no source level information is required. This may for instance be used in case assessment when the relevance of a particular knife to a criminal activity is debated. For network II, comparison to reference fingerprints from the person of interest is usually required to determine the area of friction ridge skin that left the marks. In our experiment, we used video footages together with photographs taken from the fingermarks on the knives to determine the area of friction ridge skin that left the marks. An advantage of this choice is that smears and fingermarks that are not suitable for identification purposes are also taken into account. A disadvantage of this choice is that these video footages are generally not available in casework, and therefore, the probability to find fingermarks and the ability to assign the area of friction ridge skin to a mark based on this experiment are overestimated compared to case work. A further study focusing on comparing the conducted approach to an approach focusing on the quality of the fingermarks (i.e. grading the fingermarks by using a scale as proposed by Sears et al. [11] or Becue et al. [16]) is needed to point out the implications of the selected method.

A limitation of our experiment is that all donors were right-handed. For left-handed donors, we expect a difference in area of friction ridge skin that will end up on the different sides of the knife handle since the grip would most probably be a mirrored image of a right-handed grip. However, since we have taken all sides of the knife handle together by dividing the knife into the three locations handle, backside and blade in the networks proposed, we do not expect much differences between right-handed and left-handed donors. In case the difference between right-handed and left-handed donors are a topic for further research, we recommend to divide the knife handle into smaller areas (e.g. S1-S4) such that the information which area of friction ridge skin ended on which side of the handle may provide information on the handedness of the donor.

The data from the experiments presented here must be carefully considered when used in casework, to make sure the results are also being applicable to the case at hand. For example, all assumptions and evaluations described in this chapter are based on the steak knife used in the experiment. The results obtained from the experiment could also be used for knives of similar size and shape as the steak knife used in this experiment. However, if the size or the shape of the knife of interest changes to a complete different knife such as a foldable knife or a cleaver, the results may not be directly applicable since the characteristics of the knife directly influence the possible combination of grips on the knife. When using the data presented in this chapter for evaluations in real casework, a carefull consideration of the characteristics of the knife, but also the activities at stake, the conducted experiment and the assumptions that were made is required.

To be able to use the Bayesian networks for the evaluation of the findings, it is of great importance that all conditional dependencies between the variables are carefully considered. Although these dependencies may result in a complex network, ignoring dependencies that in real life exist may result in an overestimation of the likelihood ratio. For example, if the dependency between the area of friction ridge skin due to the shape of a hand was ignored in our research, this would result in an unjustified higher likelihood ratio. On the other hand, an underestimation of the likelihood ratio is also possible when probabilities are assigned to combinations of area of friction ridge skin on particular locations on the knife for which is known they are impossible to achieve. If these combinations received a probability, they are considered feasible and combinations that are actually feasible receive a lower probability, resulting in an underestimation of the likelihood ratio. Therefore, we would like to stress the importance of a careful consideration of the dependencies between variables and a careful consideration of the states or combinations of states that are not feasible. Additionally, assigning the prior probabilities to improbable combinations should also be discussed in court since this also directly influences the likelihood ratio.

The likelihood ratio values resulting from our calculations can be considered relatively low ($0.01 \leq LR \leq 50$) resulting in a slight or moderate support for one of the propositions [13]. A reason for this is that our experimental sample size was relatively small, i.e. 24 participants for each scenario. Due to the number of possible states for the nodes, this results in many states which stay unobserved in our small sample size while they may receive observations when using a larger sample size. Although the range of LRs obtained in this study might be considered relatively low, this does not mean that an evaluation of fingermarks given activity level propositions is not valuable. This is because the issue that is being addressed at activity level is generally much closer to the deliberations of the court than any source level issues. Depending on the sample size, the data collection strategy, the uniqueness of particular observations for certain activities on the object of interest and other factors, the likelihood ratio value may increase (or decrease) for other scenarios or other objects of interest. Furthermore, when combining the results for fingermarks given activity level propositions together with all other evidence present in a case, this relatively 'low' LR value may still add a considerable value to a case and help a jury or judge in their decision.

In this study, we present an approach to evaluate fingermarks given activity level propositions in cases like the Meredith Kercher case by using Bayesian networks and a case specific experiment. From the current trends within the field of forensic science, a focus on questioning how and when evidence ended up on a surface is observed [17]. In our opinion, this new focus on the activity that led to the deposition of traces is also relevant for fingermark evidence. The use of Bayesian networks and case specific experiments to assign the probabilities to transfer, persistence, and recovery of friction ridge skin marks shows great potential for the evaluation of fingermarks given activity level propositions in casework. With the use of this powerful and transparent method, a scientist is able to assist the court in addressing and evaluating their findings given the relevant activity level questions in a case.

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3

4

A study into fingermarks at activity level on pillowcases

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ABSTRACT

In this chapter, we describe a promising method to evaluate the location of fingermarks on two- dimensional objects, which provides valuable information for the evaluation of fingermarks at activity level. For this purpose, an experiment with pillowcases was conducted at the Dutch music festival Lowlands, to test whether the activity 'smothering' can be distinguished from the alternative activity 'changing a pillowcase' based on the location of the touch traces left on the pillowcases. Participants carried out two activities with paint on their hands: smothering a victim with the use of a pillow and changing a pillowcase of a pillow. The pillowcases were photographed and translated into grid representations. A binary classification model was used to classify the pillowcases into one of the two classes of smothering and changing, based on the distance between the grid representations. After applying the fitted model to a test set, we obtained an accuracy of 98.8%. The model showed that the pillowcases could be well separated into the two classes of smothering and changing, based on the location of the fingermarks. The proposed method can be applied to fingermark traces on all two- dimensional items for which we expect that different activities will lead to different fingermark locations.

4.1. Introduction

Forensic scientists are increasingly interested in the interpretation of evidence at activity level [1]. Activity level questions focus on the activity that led to the deposition of the evidence [2]. However, for fingermark evidence, little attention has been devoted to interpretation at activity level. Most studies on fingermark evidence focus on the interpretation at source level, while the court frequently has to address questions at activity level.

An example of cases in which activity level questions related to fingermarks may arise are criminal cases with a pillow as the object of interest: was the pillow used to smother a victim?[1] By definition, smothering is a form of suffocation caused by an obstruction of the throat and mouth [3]. In homicidal smothering cases, an item often used to obstruct the airways is a pillow [4]. In these cases, the victim usually shows very few specific marks or traces, unless the victim resisted forcefully. This is often problematic, since smothering victims usually tend to be young, old, disabled or incapacitated by illness or drugs [4]. Nowadays, activity level analysis of textile fibres can be used as trace evidence in smothering cases [5]. However, the transfer of the fibres depends on several factors such as the shedder capacity of the fabric and the nature of the impact. In these cases, it would be of great interest to be able to evaluate the fingermarks on the pillowcase at activity level as well.

For fingermarks, the area where an item is touched will potentially contain valuable information for the evaluation of propositions at activity level. In previous research [6], we identified the variable 'location of the fingermarks' as an important feature that may provide information about the manner of deposition of the fingermarks. The location where a surface is touched depends on the activity carried out, and therefore the location of the fingermarks may differ between activities. Until now, the location of fingermarks in relationship to activity level questions has not been addressed in any literature and it is not known whether it is possible to derive conclusions on activity level from fingermark patterns. More importantly, an objective method to study the location of fingermarks on items is lacking.

The aim of this study was to create a method to analyse the location of fingermarks on two-dimensional items. For this purpose, we used pillowcases as the object of interest to study whether we could distinguish the activity 'smothering' from the alternative activity of 'changing a pillowcase' based on the location of the touch traces left by the activities. To do so, we performed an experiment on the Dutch music festival Lowlands, in which participants performed two activities with paint on their hands: the activity of smothering with the use of a pillow and the alternative activity of changing a pillowcase of a pillow, representing replacing the bedding. The pillowcases were photographed and a method was designed to extract the location features of the fingermarks left on the pillowcases. A binary classification model was used to classify the pillowcases into one of the two classes, smothering and changing, based on these location features. The result is a promising model for the evaluation of propositions at activity level, based on trace locations, that could be applied to two-dimensional objects in general.

[1] A search in a database consisting of randomly selected Dutch verdicts (`www.rechtspraak.nl`) resulted in at least twenty cases in the last five years in which this question was relevant. Case example: Rb Rotterdam 27 November 2014, ECLI:NL:RBROT:2014:9661.

4.2. Materials and methods experiment

4.2.1. Participants

A total of 176 visitors of the Dutch music festival Lowlands—which took place from 19/08/2016-21/08/2016—voluntarily participated in the experiment. Three participants stopped during the experiment for personal reasons. Ethical approval was obtained from the Human Research Ethics Committee (HREC) of the Delft University of Technology. The fingermarks collected during the experiment were not suitable for identification by the friction ridge pattern due to the use of an excess amount of paint.

4.2.2. Experimental design

A within-subjects design was used in which every participant was assigned to the same experimental tasks, namely performing both the smothering and changing scenario once. We used across-subjects counterbalancing for the order in which the scenarios were performed by changing the order of the scenarios every hour, for a total experimental time of 24 hours.

4.2.3. Materials

The barcode stickers used were produced on 63.5 x 29.6 mm acetate silk labels. To mark the location where the pillows have been handled, UV fluorescent skin friendly paint of the brand PaintGlow Neon UV Face and UV Body Paint was applied on the hands of each participant, in the colours blue (AA1B03), pink (AA1B04) and yellow (AA1B01). Black, 100% cotton pillowcases (70 x 60cm) by the name of DVALA and pillows (70 x 60cm) by the name of AXAG, both purchased at IKEA, were used. The pillows were covered with a water-resistant pillowcase[2], and the mattress was covered with plastic foil to prevent paint cross-contamination.

For the experiment, two separate bedrooms were created. Next to the beds, tables were situated on which a pillowcase was placed. In the smothering scenario, a life-sized dummy of ±1.80 m with a wooden head represented the victim. The dummy was positioned in the bed under a blanket, with its head on a pressure sensor such that the pressure the volunteers exercised to smother the victim was measured. A script (Matlab®) written by the TU Delft was used to measure the performed pressure over time to check whether the participants put enough effort into smothering the victim[3]. The carried-out scenarios were recorded with a Logitech C615 HD webcam in each bedroom.

The pillowcases were photographed in a light proof photography tent for optimal UV light results. A frame with the exact dimensions of the pillowcases was used to stretch the pillowcase to remove creases. The pillowcases were photographed with a Nikon D800, 60mm/2.8 lens, illuminated with UV light of wavelength 320–400 nm with the use of a Lumatec.

4.2.4. Experimental protocol

At the start of the experiment, each participant was assigned a personal mentor who guided the participant through the experiment and tried to identify any signs of discomfort during the performance of the scenarios. In case this occurred during a scenario, the scenario was ended,

[2] https://www.zorgmatras.com/waterdicht-kussen.html
[3] For further information on the pressure software, we refer to Arjo Loeve, department Biomechanical Engineering, Delft University of Technology. Email: a.j.loeve@tudelft.nl.

and the participant went directly to the debriefing. The personal mentor started with a briefing and handed the participants four personal barcode stickers, used to mark the pillowcases used in the experiment. After providing informed consent, the participant was asked to fill in a digital questionnaire that was linked to his/her personal barcode by scanning with a hand scanner.

After closing the questionnaire, the participants' hands were covered with fluorescent paint using paint rollers to obtain an equal distribution of paint over the hands. Three different colours were applied to distinguish the marks of the fingers (blue), the palm (pink) and the thumb (yellow). Afterwards, the personal mentor brought the participant to the first scenario (depending on the time slot) and its corresponding bedroom. Between the scenarios, the participant washed his/her hands, and new fluorescent paint was applied.

In bedroom A, where pillowcases are being changed, the pillow covered in a water-resistant pillowcase was positioned on the bed. On the table next to the bed, a clean, unfolded pillowcase with its opening to the left was placed. The participant was instructed to change the pillowcase on the pillow. The instruction was to carry out this activity in the exact same way as he/she would do at home, while attempting to ignore the paint on their hands. After the scenario was carried out, the appropriate barcode stickers were placed on the pillowcase, in a corner where no paint was present. It was decided that the front side was going to be the upper side of the pillow as left on the bed. Next, the pillowcase was removed from the pillow and placed on a clothes hanger to dry. The plastic pillowcase, the foil on the mattress and the table were cleaned between experiments to prevent paint cross-contamination.

In bedroom B, where the smothering scenario was carried out, a pillow covered in a water-resistant pillowcase and covered in a pillowcase with its opening to the left was positioned on the table. The participant was instructed to smother the dummy using the pillow and ignoring the paint on the hands. The participant was instructed to perform enough pressure until the computer showed a blue screen, marking the end of the scenario. This occurred when a previously set pressure/time ratio was obtained. When the scenario was finished, the participant left the pillow on the bed. The pillowcases were then processed as previously described for the changing scenario. After participating in the experiment, the participants were debriefed by their personal mentor.

As soon as the pillowcases were dry, pictures were taken of the front side and backside of each pillowcase under UV illumination. The UV light caused the yellow paint used for the thumbs to show green, the blue paint used for the fingers to show blue and the pink paint used for the palms to show red in the resulting images.

4.3. Image processing

4.3.1. Image pre-processing

During the experiment, we collected four pillowcase images per donor: smothering front, smothering back, changing front and changing back. The digital images were all acquired under identical conditions. The photos were edited using Photoshop CS, following the protocol described in the supplementary material, Appendix C. After pre-processing the images, all donors from whom four correct images were obtained were used for further analysis. A method to measure the location of the fingermarks left on the pillowcases had to be designed. We chose to transform each image into a grid in which the cells that contain fingermarks were marked.

4.3.2. Image processing

A software tool was developed to segment the fingermarks from the images. This segmentation process was performed in separate steps, which can be found in the supplementary material, Appendix C. The whole segmentation process resulted in two grid representations per pillowcase, one of the front and one of the back, in which the presence of fingermarks is marked.

4.4. Analysis

All analyses were conducted using the software R, version 0.99.896 [7].

4.4.1. Classification task

Formally, the purpose of classification is to assign the objects to a class based on measurements on the objects [8]. The objects in our study are the pillowcases with the two classes, smothering and changing. The image classification task can then be defined as: to which class does a pillowcase belong given the position of the fingermarks? To perform this classification task, a supervised learning algorithm is used. A part of the pillowcase data set is used as a training set to train the algorithm. For all the pillowcases in this training set, we know to which class they belong. The trained algorithm is used to predict the class of pillowcases in an unseen test set. These class predictions are compared to the known classes of the pillowcases in the test set to determine the accuracy of the model.

4.4.2. Data pre-processing

For the data pre-processing, the design shown in Figure 4.1 was used. Since the front and the back side of one pillowcase are dependent, we decided to concatenate each two sides of a pillowcase. As a result, we obtained a 20x46 grid for one pillowcase, in which the right side represents the front and the left side represents the back. The final dataset consisted of two concatenated grids for each scenario per donor.

All donors were randomly split into three subsets: a training set, a test set and a validation set. Of the total dataset, 70% is used as training set 1 and 30% is used as a test set. Training set 1 was again divided into a training set 2 (70% of training set 1) and a validation set (30% of training set 1). Training set 2 and the validation set were used to find the right data construction and the best algorithm. Herein functioned the validation set as a test set to test each algorithm we tried during this phase. After the final algorithm was found and the results were optimized, the model was trained on training set 2, and the obtained model was used to make predictions about the unseen test set.

4.4.3. Feature extraction

The location of the fingermarks had to be extracted from the grids to perform the classification task. Since it was expected that there is a higher similarity between two grids of the same class than between two grids of a different class, we decided to use a similarity measure between the grids. Each grid can be represented by a large vector in which every grid cell is translated to a vector element. The similarity between two binary vectors can be represented by a so-called similarity index [9]. The value for ranges from 0 to 1; two completely similar vectors have a similarity index of 1 and two completely different vectors have a similarity index of 0. The similarity index

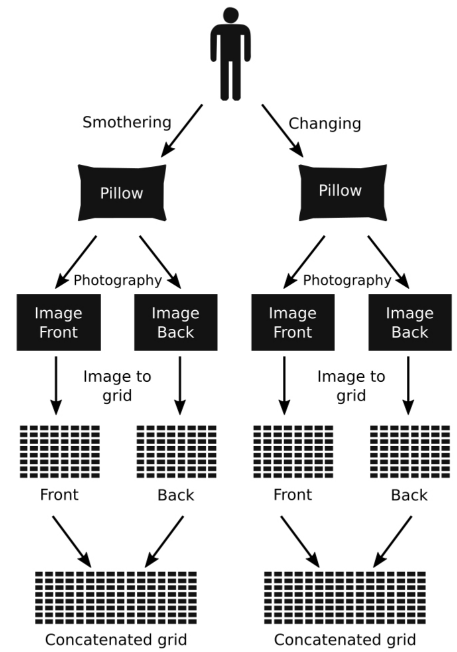

Figure 4.1: Data construction. The process results in two concatenated rasters per donor.

is based on the 2 x 2 contingency table shown in Table 4.1, in which: a represents the number of cells for which both vectors contain a 1 (fingermark); b represents the number of cells for which vector one contains a 1 (fingermark) and vector two contains a 0 (no fingermark); c represents the number of cells for which vector one contains a 0 (no fingermark) and vector two contains a 1 (fingermark); and d represents the number of cells for which both vectors contain a 0 (no fingermark).

		Vector of pillowcase 2		
		1	0	
Vector of pillowcase 1	1	a	b	$a+b$
	0	c	d	$c+d$
		$a+c$	$b+d$	n

Table 4.1: Contingency table. Values in this table are used to calculate the similarity between two pillowcases.

A similarity coefficient between two vectors can be calculated in several ways. Since we observed that the absence of fingermarks on a pillowcase also provides information on the class to which the pillowcase belongs, we chose for the simple matching coefficient of Sokal and Michener [10], which also takes the matching empty cells into account:

$$SI = \frac{a+d}{n} \tag{4.1}$$

Using the SI, the Euclidean distance d between two vectors can be expressed as:

$$d = \sqrt{1 - SI} \tag{4.2}$$

This method was used to obtain a distance measure between two grids of pillowcases. For each grid, the distances to each of the grids in the training set smothering and to each of the grids in the training set changing were calculated. As a result, each grid can be represented as a feature vector $\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$ where x_1 represents its mean distance to the training set smothering and x_2 represents its mean distance to the training set changing. A grid of a smothering pillowcase will be more similar to the grids of other smothering pillowcases than to the grids of changing pillowcases, resulting in a lower distance to the smothering training set and a higher distance to the changing training set. For the grid of a changing pillowcase, the reverse reasoning holds. Based on these distance measures, we expect that the grids of the pillowcases of both scenarios can be quite well separated.

The feature vectors of all pillowcases together form a so-called feature space and a classification rule partitions the feature space into regions [11]. In our study, we were looking for a classification rule that partitioned the feature space into the two regions smothering and changing. To determine the decision boundary between these two regions, the approach of Quadratic Discriminant Analysis (QDA) was used.

4.4.4. Classification

To construct the classification system, a quadratic discriminant analysis (QDA) classifier was used to classify each feature vector of a pillowcase into one of the classes smothering or changing. For further explanation of quadratic discriminant analysis, we refer the reader to James et al. [12].

4.4.5. Side of the pillowcase

The proposed model was built under the assumption that it was known which side of the pillowcase was used on top when smothering. Because it is highly unlikely that this information is available in forensic casework, we classified the test set without using this information. For each donor in the test set, we concatenated the two grids of a pillowcase in two ways: one of which the front side was on the left and one of which the front side was on the right, as shown in Figure 4.2. For both these concatenated grids, the distance to the set smothering and to the set changing were determined. The concatenated grid for which the distance to the training set smothering was minimal was taken to be the most likely concatenation for a smothering pillowcase; this distance is used for the value of x_1. The concatenated grid for which the distance to the set changing was minimal was taken to be the most likely concatenation for a changing pillowcase; this distance is used for the value of x_2. By comparing the concatenation order chosen by the model with the known concatenation order for the test set, we can study the ability of the model to predict the front and the back of a pillowcase.

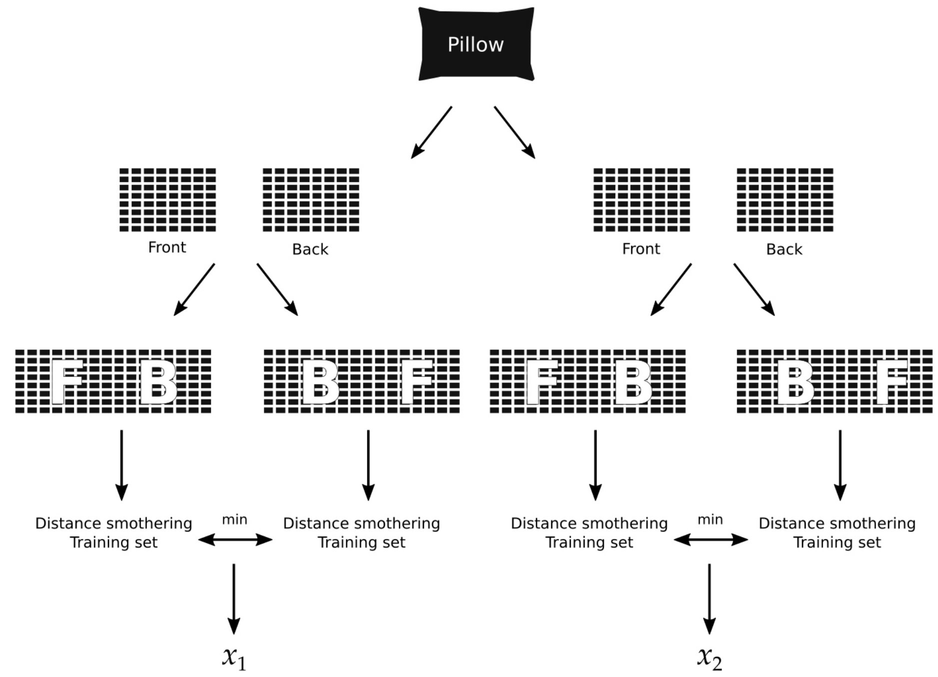

Figure 4.2: Data construction for testing the side of the pillowcase.

4.4.6. Programming in R

For the implementation of the analysis in R, the following packages were used:

- Raster for all grid computations [13];
- Ade4 to compute distance measures [14];
- MASS to perform QDA [15]; and
- MVN to test assumptions for QDA [16].

4.5. Results

4.5.1. Participants

We obtained two pillowcases each from 173 volunteers, resulting in 704 images. Unfortunately, not every image was suitable for analysis due to photography issues such as movement, incorrect lightning or creases. For these images, the quality of the image was too poor or the location of the fingermarks was shifted due to creases, and therefore these images could not be used for further analysis. For the final analysis, we selected all donors for whom all four images were determined correct according to the protocol described in the supplementary material, Appendix C, resulting in 132 donors and 528 images. Table 4.2 shows the characteristics of these 132 participants. The group consisted of 59 men and 68 women, with an age ranging from 18 to 60 years old ($M = 28.0$, $SD = 8.3$).

Characteristics of participants		n	Percentage
Sex	Men	59	45%
	Women	68	51%
	Unknown	5	4%
Age	< 30	82	62%
	31–50	43	33%
	> 50	4	3%
	Unknown	3	2%

Table 4.2: Characteristics of the volunteers who participated in the experiment.

4.5.2. Heat map

Figure 4.3 and Figure 4.4 show heat maps of the grids for the changing scenario and the smothering scenario, respectively. These heat maps show the concatenated grids of the front side and back side of the pillowcase, with the opening on the left-hand side. The heat maps show meaningful differences with regard to the location of the fingermarks between the two scenarios. The traces caused by changing a pillowcase show a random distribution over the pillowcase for both the front and the backside of the pillowcase, with a higher distribution of fingermarks around the opening of the pillowcase. The traces caused by smothering with the pillow show a high density of traces in the middle lane of the front side of the pillowcase. On the back side of the smothering pillowcases, almost no fingermarks are found, and the fingermarks that are found are mostly around the opening of the pillowcase.

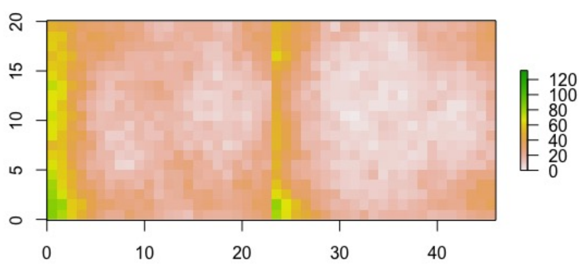

Figure 4.3: Heat map changing. Shows the heat map of the concatenated pillowcases used under the scenario changing.

4.5.3. The classification model

The 132 donors were randomly split into three subsets, a training set, test set and a validation set, as shown in Figure 4.5. Training set 2 and the validation set were used to optimally fit the model. For each pillowcase in training set 2, the distances to the training set smothering and

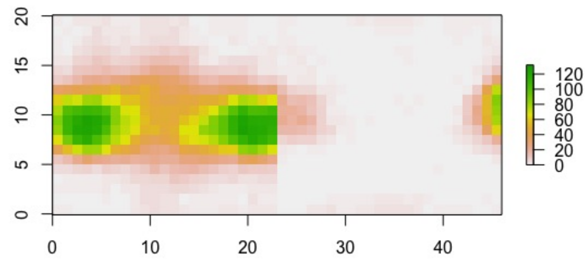

Figure 4.4: Heat map smothering. Shows the heat map of the concatenated pillowcases used under the scenario smothering.

to the training set changing are calculated. The resulting feature space is shown in Figure 4.6. The red dots represent the changing pillowcases, and the blue dots represent the smothering pillowcases. Figure 4.6 shows that the two classes smothering and changing are distributed into two reasonably separate regions.

A QDA classifier assumes the classes to be multivariate normally distributed. We have tested this assumption using the Mardia test and QQ plots (see the suppledropbomentary material, Appendix C). From the Mardia test, it appeared that the data were not multivariate normal within the classes. Because multivariate outliers are a reason for violation of the multivariate Gaussian assumption [16], we studied the QQ plot of each class. It appeared that there are a few outliers that distort the normality assumption. Besides these outliers, the data follow a normal distribution, and we assume that with a bigger dataset, the assumption of a multivariate Gaussian distribution for each class is met and QDA can be applied. A summary of the resulting QDA model is available in Appendix C.

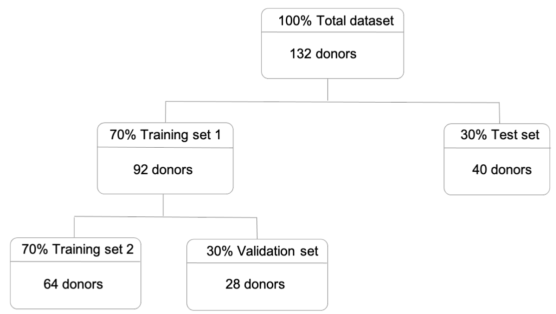

Figure 4.5: Subsets of total dataset. Division of donors into three separate subsets.

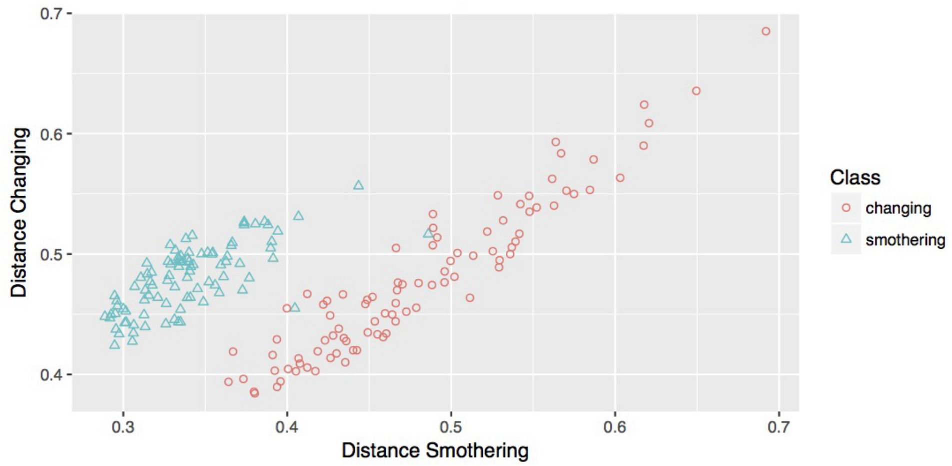

Figure 4.6: Feature space. Shows the distribution of the pillowcases based on the distance measures.

4.5.4. Evaluation of the model

Table 4.3 summarizes the results of classifying the observations in the test set with the QDA classifier. The model classified 39 of the 40 pillowcases correctly, representing a model accuracy of 98.8%. Of particular interest are the errors obtained when applying the model. Table 4.3 shows that the error is a smothering pillowcase that is classified as a changing pillowcase. When looking more closely at the pictures and video footings of this false negative, we found that the donor rotated the pillow 45 degrees before starting smothering, resulting in a trace pattern exactly 45 degrees rotated from the pattern observed in the heat map for smothering.

Test set	Changing	Smothering
Changing predicted	40	1
Smothering predicted	0	39

Table 4.3: Confusion matrix for the test set using the QDA classifier.

4.5.5. Likelihood ratio

Since classification using QDA is based on the posterior probability $Pr(Y = k|X = \mathbf{x})$ for k = (smothering, changing) and $\mathbf{x}$ is a feature vector of the corresponding pillowcase, a likelihood ratio can be determined for each pillowcase. With the use of a prior probability of 0.5 for each class, the posterior probability is equal to the likelihood ratio. Therefore, the model directly provides a likelihood ratio for each pillowcase in the classes smothering and changing.

The distribution of the likelihood ratios obtained from the total set can be observed in Figure 4.7, in which the range of the $\log_{10} LR$ values can be seen on the x-axis. This figure shows that the likelihood ratios for the classes changing and smothering are almost perfectly separated. However, there are smothering pillowcases that obtain a likelihood ratio in favour for the scenario changing, resulting in misleading evidence in these cases [17]. These are the three misclassified smothering pillowcases discussed previously. Furthermore, from the distributions, we observe that the likelihood ratios reach rather extreme values. A reason for this may be that the likelihood ratio values provided by the model may be sensitivy to extrapolation errors, which will be discussed further in the discussion section.

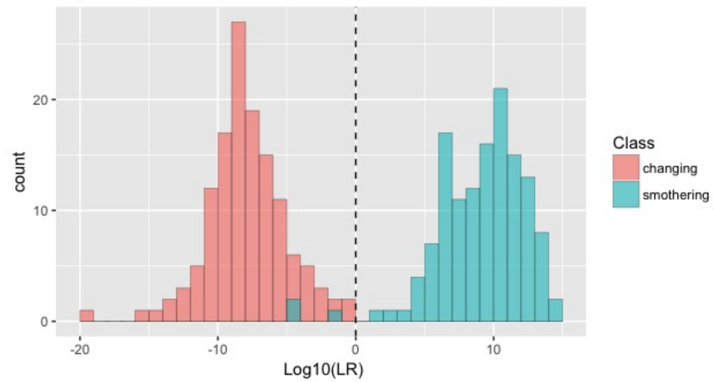

Figure 4.7: Likelihood ratio distribution. Shows the calculated $\log_{10} LR$ for each pillowcase

4.5.6. Side of the pillowcase

Table 4.4 shows the results of predicting the order of concatenation of the grids in the test set. The results show that the front and back side of the smothering pillowcases were all predicted correctly. The front and back side of the changing pillowcases are wrongly predicted in 37.5% of the cases. This can be explained by the fact that the front and the back side of the changing pillowcases show similar distributions of fingermarks, whereas the front and the back side of smothering pillowcases show very different distributions of fingermarks.

	Correct predicted order	Incorrect predicted order
Changing	25	15
Smothering	40	0

Table 4.4: Results of predicting the order of concatenation.

4.6. Discussion and conclusion

The purpose of this study was to create a method to analyse the location of fingermarks on two-dimensional items. For this purpose, we used pillowcases as the object of interest to study whether the activity of smothering with a pillow can be distinguished from the alternative activity of changing a pillowcase, based on the fingermarks left by the activity. The results of our classification model show that the fingermark patterns caused by smothering with a pillow can be well distinguished from the fingermark patterns caused by changing a pillowcase based on the location of the traces, with a model accuracy of 98.8%. The results support the expectation that the location of the fingermarks on a pillowcase provides valuable information about the activity that is performed with it.

The proposed model misclassified one pillowcase for belonging to the changing class when it actually belonged to the smothering class. When studying this pillowcase, we learned that the resulting trace pattern showed a rotation of 45 degrees compared with the trace pattern on the other smothering pillowcases. This was the only pillowcase in the test set for which this pattern is observed, and the model directed us to this exception. After examining the training set and the validation set, we found two other pillowcases showing this trace pattern. We expect that with a larger sample size, these rotated pillowcases will be observed more often, resulting in a larger number of rotated pillowcases in the training set. Consequently, the learning algorithm based on the training set will probably learn that the rotated variant also belongs to the class smothering, resulting in a model that might predict the right class for the rotated variant. Another possibility might be to assign a third class representing the rotated variants. This might result in a classification model in which the pillowcases are classified into three separate classes: changing, smothering and rotated smothering.

In this experiment, the side of the pillowcase that was used for smothering is known. In forensic casework, this information will not be available. Therefore, we tested the pillowcases in the test set without using this information. The results show that the front and the back of the pillowcases used for smothering are determined correctly in 100% of the cases. For changing pillowcases, 62.5% of the pillowcases were correctly determined. It is not of much interest to determine the front and back of a pillowcase that is used for changing; however, it can be highly valuable to be able to determine the front and back of a pillowcase that is used for smothering, since it makes a targeted sampling for DNA possible. This information, together with the location information of the fingermarks, may provide valuable information in smothering cases, especially on the activity level interpretation of the fingermarks.

Performing the experiment at a music festival such as Lowlands allowed us to obtain many participants in only one weekend. Normally in forensic casework, it is often challenging to obtain a dataset of the size we obtained. For cases in which this might be challenging, citizen science projects such as the one we performed on Lowlands may offer a solution, as also shown by Zuidberg et al. [18]. The results show a large variety of donors, and the results of the experiment can be based on a relatively large sample.

Although the results of our experiment are promising, there are some important limitations that make direct implementation in casework difficult. One drawback of practical experiments in forensic science is that it is difficult to reconstruct a realistic murder scenario. In real life, the person who is smothered will very likely resist. This could not be simulated in our experiment. Additionally, the time it takes to smother a person will be up to a few minutes [19]. Due to the fact that the experiment had to be suitable for a festival and we did not want to emotionally and

physically burden participants excessively, we used a smothering time of around 45 seconds, depending on the pressure performed. Another point to mention is that we used paint for the detection of the fingermarks. The resulting paint traces are not directly comparable to the results when visualizing fingermarks with the use of visualization methods. Further research should reveal whether the model is also applicable to visualized fingermarks. An additional limitation is that we only considered the two activities smothering and changing, both independent of each other. In real life, a pillowcase that is used for smothering may contain other fingermarks caused by changing the pillowcase and other activities. It would be of interest to study these combined activities to see whether it is possible to select the fingermarks that resulted from smothering to make targeted DNA sampling possible.

The likelihood ratio values for the pillowcases obtained with our model are rather extreme. These are not the likelihood ratio values we expect to obtain in real cases. The likelihood ratio values provided by the model may be sensitive to extrapolation errors since we have no proof of the applicability of QDA beyond our dataset [20]. The assumptions we have made are only based on a limited dataset. A solution for this may be to calibrate the likelihood ratio system of the model, which can be done in several ways [21]. Before the LR's provided by this model could be applied in casework, further research on calibrating the likelihood ratio system is recommended.

A limitation of the proposed classification model is that the training set must consist of data that has exactly the same dimensions as the data in the test set. For example, the resulting model based on a training set consisting of pillowcases with dimensions 60 cm x 70 cm may not directly be applicable to pillowcases with a different ratio because the size of the fingermarks does not change in the same ratio as the size of the pillows. Further research is necessary to overcome this problem.

Of great importance is that the resulting model is not only limited to pillowcases; we propose a promising model for studying trace locations at activity level that could be applied to two-dimensional objects in general. This means that the model can be applied to all two-dimensional items for which we expect that different activities will lead to different locations of fingermarks. As long as the traces can be visualized, the proposed method can be trained to classify the items into separate classes based on the location of the traces. The only difference is that the learning algorithm of the model must be trained with a new training set consisting of grids representing these new two-dimensional objects. In the future, the method may even be adjusted to account for studying fingermark locations on three-dimensional objects. This is a recommendation for further research.

For the analysis of fingermarks at activity level, this study provides an important step forward. Until now, many of the variables that provide information for fingermark evaluation at activity level have not been studied yet, and their probabilities can only be based on expert experience. We showed an example of how the variable location can be studied with the use of an experiment. This information can be implemented in a Bayesian network to study the evaluation of fingermarks at activity level in casework [6].

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5

A study into evaluating the location of fingermarks on letters

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ABSTRACT

In Chapter 4, we proposed a model for evaluating the location of fingermarks on two-dimensional items. In this chapter, we apply the proposed model to a dataset consisting of letters to test whether the activity of writing a letter can be distinguished from the alternative activity of reading a letter based on the location of the fingermarks on the letters. An experiment was conducted in which participants were asked to read a letter and write a letter as separate activities on A4- and A5-sized papers. The fingermarks on the letters were visualized, and the resulting images were transformed into grid representations. A binary classification model was used to classify the letters into the activities of reading and writing based on the location of the fingermarks in the grid representations. Furthermore, the limitations of the model were studied by testing the influence of the length of the letter, the right- or left-handedness of the donor and the size of the paper with an additional activity of folding the paper. The results show that the model can predict the activities of reading or writing a letter based on the fingermark locations on A4-sized letters of right- handed donors with 98.0% accuracy. Additionally, the length of the written letter and the handedness of the donor did not influence the performance of the classification model. Changing the size of the letters and adding an activity of folding the paper after writing on it decreased the model's accuracy. Expanding the training set with part of this new set had a positive influence on the model's accuracy. The results demonstrate that the model proposed in Chapter 4 can indeed be applied to other two-dimensional items on which the disputed activities would be expected to lead to different fingermark locations. Moreover, we show that the location of fingermarks on letters provides valuable information about the activity that is carried out.

5.1. Introduction

Focus on the activity that was carried out during the deposition of evidence has recently become an important aspect in the field of forensic science [1, 2]. Establishing a link between the donor and the crime scene by determining the source of the trace is often not sufficient to determine what happened at the crime scene. Frequently, the question in court is about the activity that led to the deposition of the traces, which requires the use of activity level propositions instead of source level propositions [3]. For fingermark evidence, the evaluation of activity level propositions is a rather unexplored territory. However, recent research has shown that evaluating fingermarks given activity level propositions may add valuable information when one is reconstructing a crime [4].

An important variable for the evaluation of fingermarks at activity level is the location of the fingermarks on the object of interest. De Ronde et al. [5] presented a model for evaluating fingermark locations on pillowcases in relationship to the activity level questions of whether the pillowcase was used for smothering or was simply changed. The study proposed that this model could be applied to all two- dimensional items for which it is expected that different activities result in different fingermark locations. An interesting application for this model is the evaluation of the location of fingermarks on handwritten letters since it might be expected that different activities—such as writing and reading—leave fingermarks on different locations and that the location of fingermarks on a letter can be used to determine what activity has taken place.

Although examinations of handwritten documents seem less relevant as a forensic discipline in the digital world, a study into the demand for document examination showed that this may not be the case [6]. Besides cases of fraud or counterfeiting, handwritten document examination is still considered very important in counter-terrorism because terrorists appear to prefer to use handwritten texts to avoid digital traces. Handwritten document examination is also still considered relevant when the authenticity of suicide notes is questioned. An example of this is the case R v. Stephen Port [7], in which Port was convicted of four murders. In one of these murders, Port left a suicide note next to the victim in an attempt to divert suspicion. Another application of handwritten document examination is found in cases involving illegal drugs. Evidence collected in these cases regularly includes handwritten notes describing the manufacturing steps for the synthesis of drugs[1]. For all these cases, it might be relevant to determine who wrote the notes or letters discovered at the crime scene. In cases regarding handwritten documents, a plausible alternative explanation for the presence of fingermarks on letters may be the activity of reading the letter instead of writing the letter. The current approach for evaluating these types of questions about handwritten documents is to perform a handwriting examination [8]. We propose a complementary innovative approach: the evaluation of the location of the fingermarks on the letter.

This study investigates whether the model proposed by de Ronde et al. [5] to analyze the location of fingermarks could also be used to distinguish the activity of writing a letter from the alternative activity of reading a letter. For this purpose, we designed an experiment in which participants carried out two tasks: reading a preprinted letter and writing a letter. The fingermarks were visualized using conventional visualization techniques for fingermarks on paper. Afterwards, the binary classification model proposed by de Ronde et al. [5] was used to cate-

[1] Case example: Rb Gelderland 20 December 2018, ECLI:NL:RBGEL:2018:5606. Available via `www.rechtspraak.nl`, a database consisting of randomly selected Dutch verdicts.

gorize the letters into the classes of writing and reading. In this study we have focussed only on the fingermarks visualised and not any palm marks that have potentially been left during writing, normally referred to as writers palm. This model is based on the distance between grid representations of the letters and classifies each grid into one of two classes that represent an activity by using quadratic discriminant analysis. The model was first trained using a training set consisting of written and read letters. The trained model was then used to predict the class of an unseen test set.

The previous study of this model on pillowcases had a few limitations. First, the objects in the training set were created by exactly the same protocol as the objects that were tested. Furthermore, for pillowcases, it was not deemed relevant to study the difference between left- and right-handed donors since the activities of smothering and changing were carried out using both hands. However, for written letters, the handedness of the donor may be an important factor. In this study, the limitations of the model were investigated by testing the influence of the length of the letter, the left- or right-handedness of the donor and the size of the paper with an additional activity of folding the paper on the model's performance.

5.2. Materials and methods

5.2.1. Experimental design

The study is divided into two experiments. In the first experiment, we studied the possibility of differentiating between the two activities of writing and reading based on the fingermark locations present on A4-sized letters for right-handed donors. For this experiment, we used a dataset of 84 right-handed donors who wrote a letter of regular length on A4-sized paper and divided this set into a training set (70%) and a test set (30%) by random selection. The training set was used to train the classification model, and the unseen test set was used to study the performance of the model. We also tested the classification performance of the model when only the front side of the letter was used to determine the influence of the back side of the letter on the classification performance.

To study the limitations of the model for different variations of the letters, we conducted a second experiment in which the classification performance of the trained model based on A4-sized letters of regular length for right-handed donors was tested on three extra test sets:

a) a test set consisting of 13 right-handed donors who wrote a full-page letter;
b) a test set consisting of 12 left-handed donors, of whom two wrote a full-page letter; and
c) a test set consisting of 15 donors who used A5-sized paper and folded their letters after writing them.

5.2.2. Experimental protocol for A4-sized papers

A total of 110 students of the Amsterdam University of Applied Sciences read a letter on A4-sized paper and wrote a letter on A4- sized paper. The participants were first presented with a letter printed on one side of the paper that was placed on a table. The participants were asked to pick up the letter and read it. This letter was printed by a printer that was loaded with clean, brand-new paper by a person wearing gloves. Next, the participant was given a new, blank sheet of clean paper on which the participant was asked to write. Since it was observed that the letters written by the participants were mostly the length of half an A4-sized paper, we asked 15 participants to write a letter that was the length of a full A4-sized paper.

To visualize the fingermarks, the letters were treated with indanedione followed by ninhydrin. The results of one donor were excluded from the dataset due to heavy staining on a letter as a result of incorrect application of the visualization method. After each treatment, the letters were documented using a scanner and edited using Photoshop CS by cropping the images and adjusting the brightness for optimal contrast between the fingermarks and the background. The custom-made software tool Lexie translated the pictures into grid representations using a segmentation process, as described by the supplementary material, Appendix C. A grid representation of 15x20 cells was used, which was found to be the optimal grid size.

5.2.3. Experimental protocol for A5-sized papers

To study the influence of the size of the paper on the performance of the model, an existing dataset consisting of grids representing A5-sized paper was used[2]. For this experiment, 15 participants were asked to perform three tasks: to read a letter printed on A5-sized paper, to write a threatening letter on A5 sized-paper and to write a love letter on A5-sized paper. The experimental protocol used for reading the letter was the same as that described in Section 5.2.2, whereas in the protocol for the writing scenario, an extra step of folding the paper was carried out by all participants after they finished writing. For the visualization of the fingermarks, the paper was treated with indanedione followed by ninhydrin and an additional treatment with physical developer. These letters were photographed instead of scanned, and the photographs were manually transformed into a grid representation of 15x20 cells.

5.2.4. Materials

For the A4-sized papers, clean regular white paper of the brand Canon Black Label Zero was used. For the A5-sized papers, clean, ruled paper of the brand Staples was used. For the development of the fingermarks, 1,2-indanedione, ninhydrin and physical devel- oper were used. Indanedione solution was prepared by mixing 8 mL stock solution of ZnCl2 with 100 mL of 1,2-indanedione stock solution (100 mL), which results in an IND-Zn solution (7,4% v/v). The stock solution of ZnCl2 is prepared by adding 0.8 g ZnCl2 to 10 mL EtOH, to which 1 mL ethyl acetate and 190 mL HFE 7100 was added. The stock solution of 1,2-indanedione is prepared by mixing 1.0 g 1,2-indanedione with 60 mL ethyl acetate, to which 10 mL acetic acid and 900 mL HFE 7100 are added and stirred for 20 min. The letters were immersed in the solution and air dried for 2 min. Ninhydrin solution was prepared by mixing 5g of ninhydrin with 45 mL of ethanol, 2 mL of ethyl acetate and 5 mL acetic acid, to which 1L of HFE7100 was added. The letters were immersed in the solution and air dried for 2 min. The A5-sized documents were additionally treated with the physical developer technique as described by Wilson et al. [9]. All solutions were prepared freshly before use, from pre-weighed reagents except the silver nitrate. The application of the developer solution occurred on a slow shaking device in order to circumvent silver deposition on the bottom of the container. All the glassware was salinized before use, to prevent silver deposition on the slightly acidic surface of the glass. ZnCl2 (>99%), EtOH (absolute, >99%), Ethyl acetate (>98%) were obtained from Sigma Aldrich (Zwijndrecht, NL). HFE 7100 was obtained from 3M (Delft, NL). 1,2-indanedione (99%) was obtained from BVDA (Haarlem, NL). Silver nitrate, maleic acid, iron nitrate monohydrate, ammonium iron sulfate hexahydrate and citric acid

[2] For the A5-sized data, we have only used the grid data that were generated from this study.

monohydrate were obtained from Merck & Co (Darmstadt, Germany). n-Dodecylamine acetate was obtained from ICN/Hicol (Aliso Viejo, CA) and Synperonic N from BDH/VWR (Amsterdam, the Netherlands).

5.3. Analysis

All analyses were conducted using the software R, a freely available software for statistical computing, version 0.99.896 [10].

5.3.1. Construction of the datasets

For the data pre-processing, we used the design shown in Figure 5.1 for both the datasets of A4-sized papers and A5-sized papers. Each picture was transformed into a grid representation of 15x20 cells. In the grid representations, the presence of a fingermark in a cell is denoted by a 1 and the absence of a fingermark in a cell is denoted by a 0, resulting in a binary grid that represents the picture. Because the front side and the back side of each letter are considered dependent, we decided to concatenate the grids into a 30x20 grid representing one letter, of which the left side represents the front side of the letter and the right side represents the back side of the letter. The final datasets consisted of one concatenated grid for each scenario per donor.

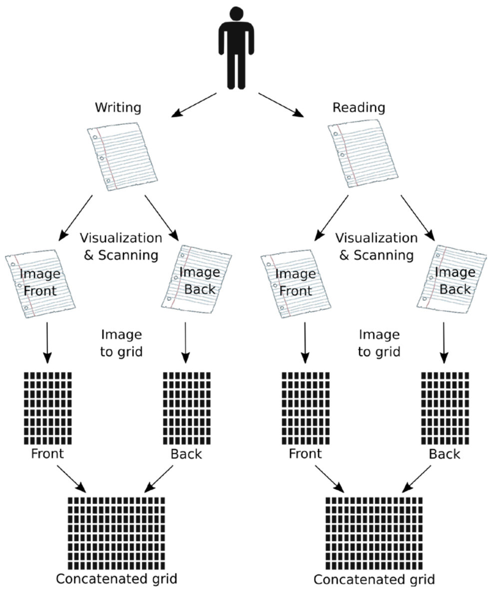

Figure 5.1: Data construction of the grids representing the letters.

5.3.2. Visual analysis

In order to visualize the location of the fingermarks on the paper for the two scenarios reading and writing, we make use of heat maps. A heat map is a graphical representation, in which the distribution of fingermarks for all grids of one scenario is visually shown by the use of colors. From a heat map, the observed fingermark locations that are characteristic for each scenario can directly be observed.

5.3.3. Classification task

The purpose of the classification model we used is to assign the objects (letters) to a class (writing or reading) based on the location of the fingermarks on the letter. This is done by training the model with the use of a training set, for which for every letter is known to which class the letter belongs. The trained algorithm is then used to predict the class of letters in an unseen test set. The accuracy of the model is determined by comparing the model predictions of the test set to the known classes of the letters in the test set. Figure 5.2 shows the structure of the datasets. In the first phase of testing, we used the training set consisting of 59 right-handed donors (denoted in gray in Figure 5.2) to train the classification model. An unseen test set consisting of 25 right-handed donors (also denoted in grey in Figure 5.2) was used to study the performance of the model. The limitations of the model were studied by testing test sets consisting of different variations of the letters to see the performance of the model trained on right-handed A4-sized letters of regular length on variations of this data, denoted by test sets A, B and C in Figure 5.2.

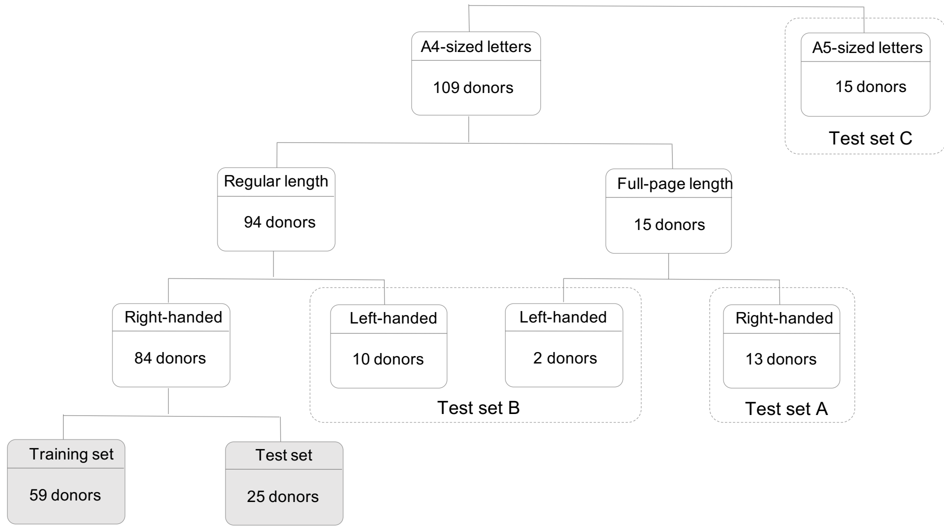

Figure 5.2: Structure of the dataset.

5.3.4. Classification model

For the analysis, we used the classification model de Ronde et al. [5] proposed. This classification model is based on a similarity and distance measure between grids. For grids that belong to the same class is expected that there is a higher similarity between them than for grids that belong to a different class. The similarity between grids is represented by the similarity index (SI) of Sokal and Michener [11]:

$$SI = \frac{a+d}{n} \tag{5.1}$$

In which a represents the number of cells for which both grids contain a fingermark, d represents the number of cells for which both grids contain no fingermark and n represents the total number of cells. The SI is used to determine the Euclidean distance (d) between two grids, which can be expressed as:

$$d = \sqrt{1 - SI} \tag{5.2}$$

This distance measure is used to determine the distance of each grid to each of the grids in the training set consisting of writing letters and its distance to each of the girds in the training set consisting of reading letters. As a result, each grid can be represented as a feature vector $\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$ where x_1 represents its mean distance to the training set of writing letters and x_2 represents its mean distance to the training set of reading letters. The classification is based on the expectation that a grid representing a writing letter has a lower distance to the training set consisting of writing letters compared to its distance to the training set consisting of reading letters, and vice versa. The feature vectors of all letters form a so-called feature space, which can be partitioned in classes with the use of a classification rule, for which we used Quadratic Discriminant Analysis (QDA). For a further explanation of QDA, we refer the reader to James et al. [12].

5.3.5. Programming in R

For the implementation of the analysis in R, the following packages were used:

- Raster for all grid computations [13];
- Ade4 to compute distance measures [14];
- MASS to perform QDA [15]; and
- MVN to test assumptions for QDA [16].
- ggplot2 to produce the figures [17]

5.4. Results

5.4.1. Right-handed donors on A4-sized paper

Figures 5.3 and 5.4 show the heat maps for the 59 right-handed donors in the training set for the scenarios of reading and writing, respectively. The heat maps show the concatenated grids of the front sides and the back sides of the letters. Figure 5.3 shows that for the read letters, the fingermarks are mostly distributed around the left and right edges, on both sides of the paper. The heat map for the written letters in Figure 5.4 shows that on the front side of the paper, the fingermarks are mostly distributed in an area on the middle top of the paper and along the left edge. The fingermarks on the middle top of the paper are caused by the placement of the right palm on the paper while writing. The fingermarks around the left edges on the front side of the paper are caused by holding the paper with the left hand. There were almost no fingermark observations on the back side of the paper.

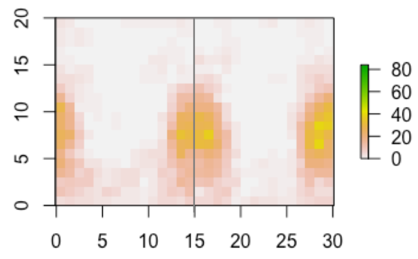

Figure 5.3: Heat map for the training set of the reading scenario.

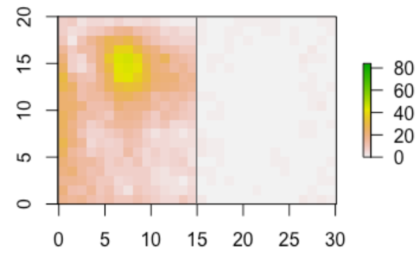

Figure 5.4: Heat map for the training set of the writing scenario.

5.4.2. The classification model

For each letter in the trainings set, its mean distances to the training set of written letters and to the training set of read letters are calculated. Figure 5.5 shows the resulting feature space, in which the distance to the training set of written letters is plotted on the x- axis and the distance to the training set of read letters on the y-axis. The red dots represent the read letters, and the blue triangles represent the written letters. Figure 5.5 shows that the two classes of reading and writing form two reasonably separate regions, raising the expectation that a classification based on a QDA classifier as used in [5] may also be appropriate for this dataset.

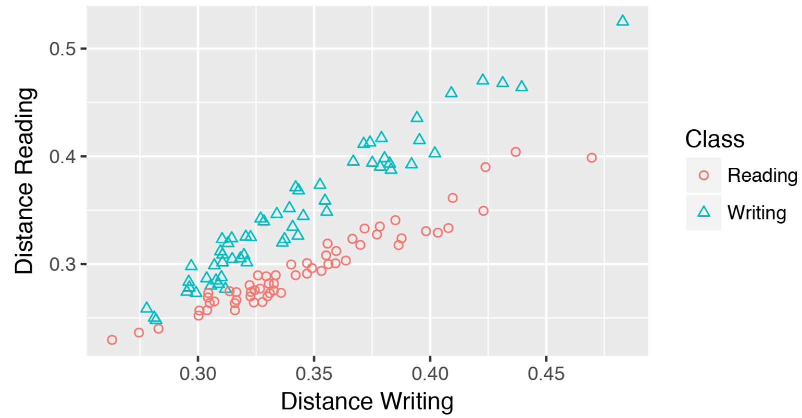

Figure 5.5: Feature space for the training set consisting of right-handed donors.

For the use of the QDA classifier, the assumption is that both classes follow a multivariate normal distribution. This hypothesis is tested with the use of the Mardia test and by studying QQ plots. The Mardia test is used to assess multivariate normality for the separate classes writing and reading based on the Mardia's multivariate skewness and kurtosis coefficients. For a further explanation of the Mardia test, we refer the reader to Kres [18]. The Mardia test result showed that the data were not multivariate normally distributed within the classes of writing

5

and reading. Because multivariate outliers may be the reason for violation of the multivariate Gaussian assumption, we studied the QQ plot of each class, a widely used graphical approach to visually evaluate multivariate normality [16]. Using a QQ plot makes it possible to directly observe outliers that may cause a violation of the multivariate normality assumption. From the QQ plot shown in Figure 5.6 for the class of writing, we observed that one outlier distorted the normality assumption. Aside from this outlier, the Mardia test shows that the data are indeed distributed following the multivariate Gaussian assumption. The QQ plot for the class of reading, shown in Figure 5.7, shows three possible outliers. Aside from the most extreme outlier in the upper right corner, the Mardia test shows that the data are also distributed following the multivariate Gaussian assumption.

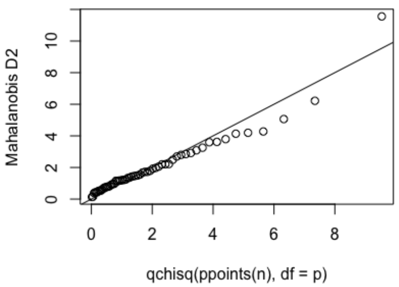

Figure 5.6: QQ plot for the class of writing.

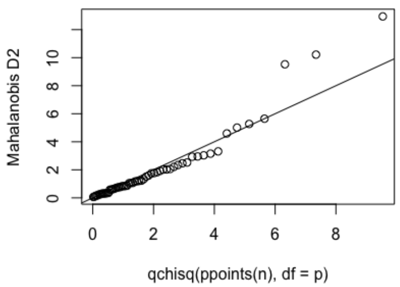

Figure 5.7: QQ plot for the class of reading.

5.4.3. Evaluation of the model

Table 5.1 shows the confusion matrix for the QDA classification of the test set consisting of 25 right-handed donors writing a letter of regular length and reading a letter. The model classified 49 of the 50 letters correctly, representing an accuracy of 98.0%. One read letter was misclassified as being a written letter. Figure 5.8 shows a visual representation of the concatenated grid of the front side and the back side of this letter, indicating that the fingermarks on this letter are around the edges, as we would expect from the heat map for read letters, but additional fingermarks are found in the middle of the front of the paper, indicated by a black circle. We expect that these fingermarks in the middle of the paper caused the model to classify it as a written letter.

Test set	Reading	Writing
Reading predicted	24	0
Writing predicted	1	25

Table 5.1: Confusion matrix for the test set consisting of right-handed donors on A4-sized paper.

Since QDA classification is based on the posterior probabilities, the use of a QDA classifier allows for the calculation of a likelihood ratio for each object present in the test set. Figure 5.9 shows the $\log_{10}$ likelihood ratio distributions for both classes of both the training set and the test set. The distributions for the classes of writing and reading are quite well separated, although

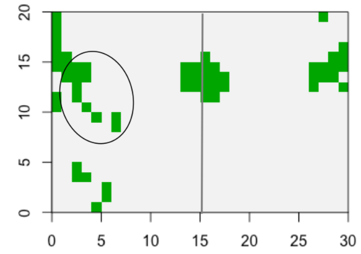

Figure 5.8: Visual representation of the grid for the misclassified read letter, in which green denotes the cells where fingermarks were present.

some letters obtain a relatively low likelihood ratio in favor of the wrong class. One of these is the letter shown in Figure 5.8, and the other three letters were present in the training set on which the model is trained. From the distributions, we observe that the likelihood ratio values reach extreme values. This will be further explained in the discussion.

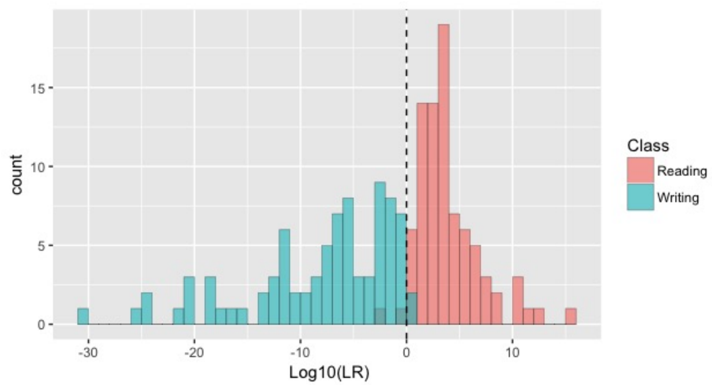

Figure 5.9: Likelihood ratio distribution for the complete dataset.

5.4.4. Only front side of the letter

Because the heat map for the writing scenario in Figure 5.4 shows that there were almost no fingermark observations on the back side of the written letters, the question of whether the model only uses the empty back side of the letter as an indication for the class of writing or reading might arise. This would make the applicability of the model questionable if the activities slightly change such that the back side of the letter also contains fingermarks in the writing scenario. To account for this, we tested the performance of the model when only using the front side of the letters. The confusion matrix shown in Table 5.2 demonstrates that when using only the front side of the letters, the model classified 48 of the 50 letters correctly, an accuracy of 96.0%. One additional read letter was misclassified as being a written letter. These results show that the model is able to classify the letters based on only the front side of the letter; however, the accuracy increases slightly when taking the dependency between the front and the back sides of the letters into account by concatenating both sides.

Test set	Reading	Writing
Reading predicted	23	0
Writing predicted	2	25

Table 5.2: Confusion matrix for the test set consisting of right-handed donors on A4-sized paper using only the front side of the paper.

5.4.5. Full-page letters (test set A)

For the analysis of the full-page letters, a test set of 13 full-page letters was predicted by the classification model trained on the training set consisting of right-handed donors who wrote letters of regular length. Figure 5.10 shows the heat map for the full-page read letters, and Figure 5.11 shows the heat map for the written letters. The heat map for the read letters shows the same characteristics as the heat map for the training set shown in Figure 5.3. The heat map for the written letters shows a somewhat different distribution of the fingermarks than the heat map for the training set shown in Figure 5.4. The area on the middle top of the paper observed for the regular length letters is more spread over the front side of the letter. However, the heat maps show somewhat the same characteristics as the heat maps used for the training set, which leads to the expectation that this test set will be quite well predicted by the model.

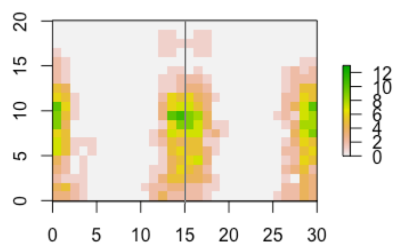

Figure 5.10: Heat map of read letters for test set A consisting of full-page letters.

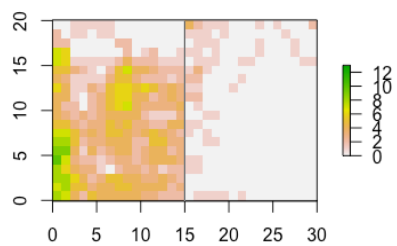

Figure 5.11: Heat map of written letters for test set A consisting of full-page letters.

Test set	Reading	Writing
Reading predicted	13	0
Writing predicted	0	13

Table 5.3: Confusion matrix for test set A consisting of full-page letters.

Table 5.3 shows the confusion matrix for the test set. The results show that the activity of reading and the activity of writing were predicted correctly in all cases, although the heat map for the written letters looked slightly different. This is because the written letters are still quite different from the read letters. Whereas for the writing scenario, fingermarks are mostly observed in the middle of the paper and almost no fingermarks are observed on the back side of

the paper, the fingermarks for the scenario of reading are still mostly placed along the edges of the paper on both sides of the paper. These results show that writing a full-page letter instead of a shorter letter on A4-sized paper does not influence the performance of the classification model.

5.4.6. Left-handed donors (test set B)

For the analysis of the letters of the left-handed donors, we used a test set consisting of 12 read and written letters, of which two donors wrote full-page letters. This test set was also predicted by the classification model trained on the training set consisting of right-handed donors who wrote letters of regular length. Since the results in Section 5.4.5 showed that the length of the letter does not influence the performance of the model, these two full-page letters were also included in the left-handed test set. Figures 5.12 and 5.13 show the heat maps for the left-handed donors for the classes of reading and writing, respectively. Figure 5.12 shows that for the read letters, left-handed donors have a similar pattern as right-handed donors. Figure 5.13 shows that for the written letters, the fingermarks of left- handed donors are distributed over the whole page, while for right-handed donors, the fingermarks were mostly distributed in an area on the middle top of the letter and along the left edge. Since the heat maps for the left-handed donors show somewhat the same characteristics as the heat maps for the full-page letters and the full-page letters were all correctly predicted, we expect that the model will also be able to predict the correct class of most of the left-handed donors.

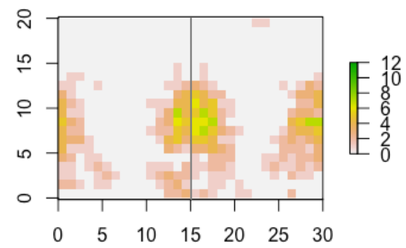

Figure 5.12: Heat map of read letters for test set B consisting of letters by left-handed donors.

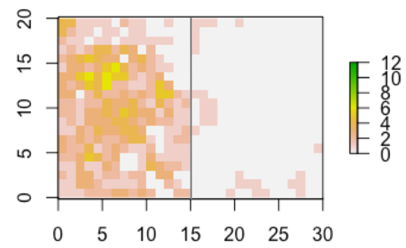

Figure 5.13: Heat map of written letters for testset B consisting of letters by left-handed donors.

Test set	Reading	Writing
Reading predicted	12	0
Writing predicted	0	12

Table 5.4: Confusion matrix for test set B consisting of letters by left-handed donors..

Table 5.4 shows the confusion matrix for the test set consisting of left-handed donors. The results show that all read letters and written letters were predicted correctly. Apparently, training the model with a dataset consisting of right-handed letters does not affect the classification of the left-handed letters, although the fingermark patterns differ for the writing scenario.

5.4.7. A5-sized letters (test set C)

For the analysis of the size of the letters, a test set consisting of 15 read letters and 30 written letters was also predicted by the classification model trained on the training set consisting of right-handed donors who wrote letters of regular length. Figures 5.14 and 5.15 show the heat maps for these A5-sized letters for the scenario of reading and the scenario of writing, respectively. Figure 5.14 shows that for the A5-sized read letters, the fingermarks are mostly distributed along the edges on both sides of the paper, as we also observed for the A4-sized read letters. Additionally, some donors placed their hands around the bottom of the paper, which was also observed for the A4-sized read letters in Figure 5.3. The heat map for the A5-sized written letters in Figure 5.15 shows that the distribution of the fingermarks is clearly different from the distribution we observed for the A4-sized written letters in Figure 5.4, for which we observed that on the front side of the paper, the fingermarks are mostly distributed on the middle top of the letter and along the left edge. For the A5-sized written letters, we observe that this area has shifted to the middle bottom of the paper and is concentrated on the entire width of the paper, and almost no fingermarks are found in the middle top area of the letter. An explanation for this may be that the palm is placed lower on the paper since the paper is smaller. Furthermore, the fingermarks around the edges caused by holding the paper with the other hand may interfere with the palm placement because the paper is narrower, so the areas almost overlap. The fingermarks on the back side of the written letters can be explained by the additional activity of folding the paper before it was put back on the table. This also differs from the heat map observed for the A4-sized written letters, since almost no fingermarks were found on the back side of the paper.

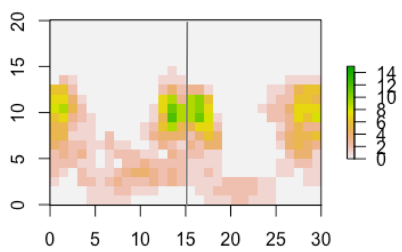

Figure 5.14: Heat map of read letters for test set C consisting of A5-sized letters.

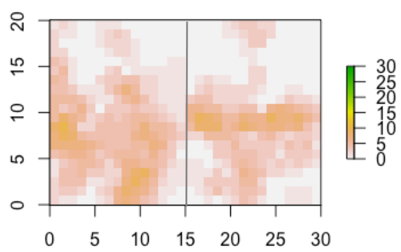

Figure 5.15: Heat map of written letters for test set C consisting of A5-sized letters.

For the classification, we tested a test set consisting of all 15 read letters and all 30 written letters (love letters and threatening letters). The confusion matrix in Table 5.5 shows that the model had an accuracy 64.5%. All 15 read letters were predicted correctly, but the model had difficulty classifying the written letters. One explanation for the model's poor classification accuracy for the A5-sized letters might be the influence of the additional post-activity of folding

the paper after writing on it. Since we expect that folding the paper mostly affects fingermarks to be present on the backside of the letter, the classification was repeated with only using the front sides of the letters. Table 5.6 shows the classification results. Although the model accuracy increased to 75.6 %, the model still wrongly predicted 11 of the writing letters. A possible explanation for this will be further explained in the discussion.

Test set A5 size	Reading	Writing
Reading predicted	15	16
Writing predicted	0	14

Table 5.5: Confusion matrix for classifying test set C consisting of A5-sized letters based on a training set of A4-sized letters.

Test set A5 size	Reading	Writing
Reading predicted	15	11
Writing predicted	0	19

Table 5.6: Confusion matrix for classifying test set C consisting of A5-sized letters based on a training set of A4-sized letters, when using the front side of the letters

One way to achieve higher accuracy for A5-sized letters may be to expand the training set consisting of A4-sized letters by adding A5-sized letters to train the model for A5-sized letters as well. For this analysis, 70% of the first 15 donors who read and wrote a love letter on A5-sized paper were added to the training set (11 donors). The remaining 30% of the donors represent the test set (4 donors), together with the extra 15 threatening letters written by the donors. For this, we assumed that there is no difference in fingermark deposition between the type of message (love or threatening) that is written. The new training set was used to train the model, and afterward, the performance of the model was tested on the unseen test set. Table 5.7 shows the confusion matrix, which indicates that five written letters are wrongly classified as read letters, resulting in an accuracy of 78.3%, which is significantly increased compared to the accuracy of 64.4% obtained for a training set consisting of only A4-sized letters.

Test set A5 size	Reading	Writing
Reading predicted	4	5
Writing predicted	0	14

Table 5.7: Confusion matrix for classifying a test set consisting of A5-sized letters based on a training set of A4- and A5-sized letters.

5.5. Discussion and conclusion

This research studied whether the model for the activity level analysis of the location of fingermarks proposed by de Ronde et al. [5] could also be used on letters to distinguish the activity of writing from the alternative activity of reading. The results have shown that the model could very well be applied to fingermarks on letters of right-handed donors to differentiate between the two activities, with a classification accuracy of 98.0%. Furthermore, we showed that the length of the written letter and the handedness of the donor did not influence the performance of the classification model. For letters on a smaller sized paper (A5) and with an additional activity of folding the paper after writing on it, the model accuracy decreased to 64.4%. If the training set consisting of A4-sized letters used to train the model is expanded with A5-sized letters, the model accuracy increases to 78.3%. These results show that the location of fingermarks on letters provides valuable information about the activity that was carried out.

Despite the fact that the heat map for the written letters of the left-handed donors showed significant differences from the heat map of written letters of the right-handed donors, all letters written by left-handed donors were correctly predicted by the model trained on right-handed donors. The difference in fingermark patterns for the scenario of writing between left- and right-handed donors may be caused by the variation in hand placement that was observed for left-handed people when they were writing letters. The reason that the classification was not affected by these different fingermark patterns is because the grids that represent the written letters of the left-handed donors still have a distinctive pattern from that of the read letters. However, care should be taken when testing left-handed donors on a right-handed–trained model. Since we tested only a small sample of left-handed donors (12), the possibility exists that not all variations of left-handed writing are incorporated in our dataset, and variations that are not represented may be classified incorrectly. To correct for this, a larger sample of left-handed donors should be tested.

The model trained on A4-sized letters wrongly predicted more than half of the written A5-sized letters. There can be two explanations: the difference in activity that is carried out and the difference in the size of the paper. An additional activity of folding the paper was carried out by the participants in the experiment with A5-sized paper, causing the appearance of fingermarks on the back side of the paper in the writing scenario. The heat maps for the A4-sized letters show that only the read letters contain fingermarks on the back side of the paper, probably causing the model to assign the class of reading to the A5-sized letters on which fingermarks are found on the back side of the paper. As a consequence, if this model is applied in casework, it is of great importance to clearly state the activity hypotheses tested to know exactly what activities are at stake. As we have shown, an additional activity may directly influence the performance of the model; if any changes are made in the activity that is proposed, for example, an extra step of folding the paper, this may directly influence the performance of the model if it is trained on a training set that does not involve this extra folding step. Thus, whether the training set should be expanded with appropriate examples of this additional activity should be considered.

Another explanation for the wrongly predicted written letters on A5-sized paper is the influence of the size of the paper. Since the model is constructed such that the training set and the test set have to contain grids of similar dimensions, the number of cells is the same for both sizes of letters (15x20), but the size of the cells differs between the grids for the A4-sized letters (1.5 cm x 1.5 cm) and the grids of the A5-sized letters (1 cm x 1 cm). However, the sizes of the fingermarks do not change when using a smaller paper, so one fingermark may fill more cells in the grid representing A5-sized paper than it does in the grid representing A4-sized paper. This means that if the size of the objects present in the training set significantly changes from the size of the object being tested, the training set will probably not be representative of the test set. One solution may be to expand the dataset with new data, as we have shown for the A4- and A5-sized letters. Another may be to not work with squared cells but to choose larger areas on the letters that are representative for the activities of reading and writing and to standardize different sizes of paper to this representation. This may be a topic for further research. For now, we propose expanding the training set so that the dimensions of the object to be tested are also represented.

The likelihood ratio values that were provided as output from our model are in a higher and lower order then expected, given the size of our dataset. Since the assumptions for the use of QDA we have made are based on a limited dataset, we have no proof of the applicability of QDA beyond our dataset, which means that the likelihood ratios provided by the system may be sensitive to extrapolation errors [19]. A solution for this is to calibrate the likelihood ratio system that results from the model. There are several methods for performing this calibration [20]. Further research is needed to determine which calibration method is most suitable for our dataset to obtain likelihood ratio values that can be directly applied to casework.

In this research, the source level information of the fingermarks is not taken into account. This means that the model is not only based on identifiable fingermarks present on the letters, but also on additional stains such as smears that were visualized. We decided to not work only with identifiable fingermarks since smears and stains are also a direct result of the activity. For example, a smear created by the placement of the palm on the paper during writing may not result in a fingermark suitable for identification. However, this smear provides information about the placement of the hand during the activity. A drawback to this is that care should be taken when using this model on visualized fingermarks: if the fingermark visualization method is not correctly applied, causing the appearance of drops or spots on the object of interest, these drops and spots will also be interpreted as marks.

In this study, we clearly separated the activities of writing and reading. In real casework, this may not always be expected. However, by studying these activities separately, we have shown that both activities cause a distinctive fingermark pattern on the letter. The heat maps show particular areas on the letter that are representative of writing traces or reading traces, making it possible to select the traces on a letter that are specific for the activity of writing or for the activity of reading. In this way, the investigation can focus on the marks that provide an indication of a certain activity, and if no identifiable fingermarks are found, a targeted sampling for DNA is possible.

With this research, we have confirmed that the model proposed [5] could very well be applied to any two-dimensional item for which it is expected that different activities lead to different fingermark locations. We now have access to a database consisting of written and read letters on A4-sized paper and A5-sized paper, and the model we have created with this database can be used in casework for evaluating the fingermark location to determine whether the letter was written or read by a particular donor. Conventional techniques to visualize fingermarks on paper were used instead of using paint, as was done in a previous study, resulting in traces that represent fingermark traces obtained in real casework. Now that we have shown that the model still works on these types of traces, the next step for implementation to casework will be to perform a pseudo-operational trial on letters that were not collected under lab conditions to see how the model performs on more realistic casework materials.

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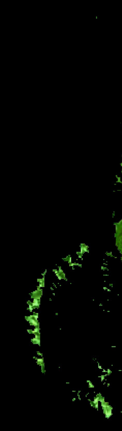
6

General discussion



The aim of this dissertation was to study how information about activities could be derived from fingermarks in a reliable way in order to be used in the forensic process. The four studies that are presented in chapters 2 through 5 show evidence that fingermarks indeed provide crucial information about what has happened at the crime scene. This research is the first step to an evaluation of fingermarks beyond the source towards activities, to be able to facilitate the court in answering relevant questions regarding how fingermarks ended up on a surface. This chapter presents a summary of the key findings, followed by a discussion on the forensic process, the value of fingermarks and a discussion on the way to go for fingermarks given activity level propositions. The strengths and weaknesses of the research are discussed, followed by the conclusion.

6.1. Summary of key findings

Chapter 2 discussed the construction of a general framework which can be used to evaluate fingermarks at activity level by using Bayesian networks. The key variables that provide a source of information on possible activities that were carried out during the deposition of fingermarks were identified. We identified transfer, persistency, recovery, background levels of fingermarks, location of fingermarks, direction of fingermarks, the area of friction ridge skin that left the mark and pressure distortions as essential variables to take into account when evaluating fingermarks given activity level propositions. Based on these variables, three configurations of a Bayesian network were presented. The first Bayesian network enables the evaluation of fingermark grips present on an item given propositions that dispute the activity that was carried out. The second focuses on propositions that dispute the actor that carried out the activity. The third configuration of the network allows for the evaluation of multiple fingermark grips present on an item. The presented Bayesian networks function as a general framework for the evaluation of fingermarks given activity level propositions, which can be adapted according to specific case circumstances.

Building on Chapter 2, Chapter 3 aimed at the application of the constructed general framework. To be able to use a Bayesian network for the evaluation of fingermarks in casework, probabilities need be assigned to the network. This chapter described how case specific experiments can be used to assign probabilities to the states of the nodes of a Bayesian network. For this purpose, an experiment was carried out in which participants used a knife for stabbing and used a knife to cut food in order to study the probabilities of transfer, persistence and recovery of particular areas of friction ridge skin to particular locations on the knife. The results are used in two different Bayesian networks to show different applications of the data. This chapter has shown great potential for the evaluation of fingermarks given activity level propositions by the use of Bayesian networks and case specific experiments to assign the relevant probabilities to the states of the nodes of the network.

Chapter 4 focussed on one of the variables that was identified in Chapter 2 as an important source of information on possible activities that were carried out: the variable fingermark location. Based on an experiment with pillows in which participants used a pillow to smother a victim and changed a pillowcase of a pillow, we developed a classification model to evaluate the location of fingermarks given activity level propositions. The results of this model show that fingermark patterns left by smothering with a pillow can be well distinguished from fingermark patterns left by changing a pillowcase, with a model accuracy of 98.8%, supporting the expectation that the location of fingermarks provide valuable information on the activity that was carried out with a pillow. This study resulted in a promising model that can be used to study the location of fingermark traces on all two-dimensional items for which it is expected that different activities will lead to different fingermark locations.

Chapter 5 described a study in which another application of the location model developed in Chapter 4 is explored, namely to study whether the model could be used to distinguish between the activities of writing a letter and reading a letter based on the location of the fingermarks present on the letters. In this study, conventional visualization techniques were used to visualize the fingermarks and the model was able to correctly classify 49 of the 50 read and written letters by right-handed donors on A4-sized paper. Furthermore, the results showed that the length of the letter and the handedness of the donor did not influence the classification performance of the model. However, changing the size of the paper, and adding an activity of folding the paper after writing on it did have an influence on the accuracy of the model; the model accuracy decreased (64.4%). This chapter showed that the model proposed in Chapter 4 is indeed applicable to a broader range of objects for which it is expected that different activities lead to different fingermark locations, under the condition that the training set is representative with regards to size and activity of the object to be tested.

6.2. The forensic process

The aim of this dissertation was to study how information about activities could be derived from fingermarks in a reliable way in order to be used in the forensic process. By forensic process, we mean the use of forensic evidence within complete process from crime scene to court. During this process, the overall goal is to obtain a transparent, reproducible and robust reconstruction of the crime based on the trace evidence, which forms the basis for a criminal trial in court. This means that the discipline of forensic science acts on the intersection between practice, science, policy and law which causes several challenges to obtain an approach of scientific endeavor within the complete process of forensic reconstruction [1]. Such a scientific endeavor is important to improve the decision-making process in forensic science, in order to minimize the misinterpretation of scientific evidence and to maximize the applicability of crime reconstruction within the criminal justice system [2]. Because decisions in forensic science are prone to the inherent subjectivity of decision making, it is important that there is transparency about how decisions are reached [3]. With this thesis, we have tried to ensure that the full potential of fingermark evidence is unlocked such that fingermark evidence can be utilized effectively and transparently in the process of forensic reconstruction to facilitate the criminal justice system at best.

6.3. The value of fingermarks

Fingermarks are commonly used as an important source of identification in criminal investigations. Although it is considered public knowledge that every time a hand touches a surface, the possibility exists that a fingermark is transferred to the surface, fingermarks are still frequently found at crime scenes. Even though the increased sensitivity of the technologies used to generate a DNA profile nowadays enable to obtain a DNA profile from touch traces [4], analyzing the features such as the general patterns and minutiae present in a fingermark still proves its value. Nevertheless, the importance of fingermarks is not only limited to source level evaluations; this thesis has shown that even for activity level evaluations, fingermarks prove their value.

An advantage of fingermarks is that generally, a fingermark serves as a direct proof of contact between a surface and the finger that left the fingermark. Although the potential of fingerprint forgery always have to be taken into account, the number of documented cases of forgeries that are committed by criminals is extremely small [5]. Since fingermarks cannot transfer indirectly without taking great effort [6], the presence of a fingermark indicates that the donor actually touched the surface, often providing a link between the donor of the fingermark and the crime scene. This is an important advantage over DNA, which can transfer indirectly via surfaces or individuals and even retransfer from one location to another [7]. For DNA evidence, alternative explanations about the presence of one's DNA at the crime scene may often be found in explanations of secondary or further transfer of DNA between surfaces and people. However, this alternative explanation can be considered irrelevant for fingermark evidence.

Furthermore, and possibly even more valuable, a fingermark may serve as a direct proof of contact between a specific finger or part of the hand and the surface on which the fingermark is found (providing that the donor of the fingermark can be determined). This information about the area of friction ridge skin that left the marks, together with the location of the fingermarks and the direction of the fingermarks, provides valuable information to reconstruct the positioning of the hand and fingers during the act of depositing the fingermarks. This new activity level information cannot be provided by evaluating any other type of evidence. For example, although new techniques allow for the determination of the type of body fluid by DNA methylation profiling [8], it is impossible to determine what area of the skin left touch DNA evidence. This dissertation has shown that this information can be provided by the evaluation of fingermarks given activity level propositions.

These advantages show that fingermarks may provide new activity level information which cannot be derived from DNA or other types of evidence. This means that the evaluation of fingermarks given activity level propositions may serve as a great addition to the already existing possibilities to evaluate forensic evidence, which will provide new opportunities for a more detailed reconstruction of the crime.

6.4. The way to go

The evaluation of fingermarks given activity level propositions

Currently, fingermarks are mainly evaluated given source level propositions to determine the origin of the fingermark. This evaluation is considered quite straightforward because it requires mainly a careful assessment of the intrinsic features (i.e. structures of the papillary lines) of the recovered material, and well accepted models, data and software are available to do so [9]. This is different for the evaluation of activity level propositions, of which we have shown that it requires the assessment of extrinsic features such as transfer, persistence, or location of the fingermarks, of which often no accepted models are yet available.

In Chapter 2, we have provided an overview of the extrinsic variables that should be considered when evaluating fingermarks given activity level propositions. Since it may be complicated to assess these additional factors appropriately due to a lack of data, a fingermark expert may feel that the evaluation of fingermarks given activity level propositions should be disregarded and he/she should stick to the evaluation of fingermarks given source level propositions. Important to note is that an evaluation of evidence given a particular level of propositions cannot by default be extended to another level of propositions [10]. An error of this type is known as a violation of the hierarchy of propositions [11, 12]. A correspondence between a fingerprint and a fingermark observed at a crime scene based on the intrinsic features of the fingermarks does normally not imply evidential value for the occurrence of a particular activity that must have led to the deposition of the fingermark at the crime scene. A thorough evaluation of the extrinsic variables is required. These extrinsic features are of no interest for a source level comparison between two fingermarks, since a source level comparison is mainly based on information about the rarity of the features in the fingermarks. As mentioned by Taroni et al. [12], the probative value of the evidence may substantially differ between source- and activity level and suggesting an assessment at source level as one at activity level places the suspect under the risk of unwarrantedly incriminating conclusions.

Current practice on fingermark evidence leaves it up to the courts to move to a higher level of propositions that will better suit their needs, even though this requires detailed knowledge about the additional variables influencing this interpretation [12]. It could be questioned whether these recipients of expert information are informed to the best of the scientist's knowledge so that no unjustified conclusions will be reached [9]. As we have seen in Chapter 2, the variables that must be taken into account when moving to a higher level of propositions when evaluating fingermarks are all rather technical aspects. This raises the question whether the court has sufficient knowledge of this matter to evaluate this evidence. Knowledge based on empirical data and experience by the expert is required to be able to properly assign probabilities to these variables [13]. This demonstrates a gap within the current practice between the information that is offered by the fingermark expert and the needs in court.

The research described in this dissertation is a first step to overcome this gap. The results have shown that by constructing a Bayesian network for a case example as described in Chapter 2, and by assigning the probabilities of this network based on empirical data from case specific experiments as presented in Chapter 3, evaluations of fingermarks given activity level propositions can be of value in cases for which there is a need in court to move from source to activity level propositions. It is the task of the forensic scientist to assist the court in asking the right questions given the available evidence, and in answering these questions such that the court can reach justifiable conclusions based on this evidence. The forensic scientist is in the position to offer relevant knowledge and advice on technical aspects about which the court itself has no expertise, but which might be relevant in specific cases. However, how can this be done in a reliable way?

Formulating the right propositions

An evaluation of evidence given activity level proposition starts with formulating the relevant activity level propositions. A number of studies have been published on how to correctly formulate activity level propositions [10, 11, 14–17]. The activity level propositions usually represent the statements of the prosecution and the defense. The activity level proposition of the prosecution is often quite straight forward, 'the suspect conducted a activity X', in which activity X is generally an activity related to the criminal offense at stake. There are two options for the defense: either it is questioned whether activity X has taken place (i.e. it is unknown whether the secured knife was used for stabbing) or it is accepted that activity X took place (i.e. it is known that the knife obtained from the crime scene was used for stabbing) [16]. In the former case, the defence may claim that the suspect used the object for daily activities and the knife was not used for an activity related to the criminal offense at all. This type of propositions was evaluated in the case example discussed in Chapter 3, in which it was questioned whether the knife retrieved from the apartment of Sollecito was the murder weapon. In the latter case, the defence may also claim that suspect used the object for daily activities. However, this will entail that someone else must have use the knife to stab the victim, since it is known that the knife was used during the crime. For this evaluation, the presence or absence of fingermarks from other donors on the knife must be taken into account, as we have shown in the Bayesian network for case example 2 presented in Chapter 2, which requires a different analysis. However, for both catagories, the central question remains whether or not the examined fingermark traces are related to the activity X at stake.

In the studies presented in Chapter 3, 4 and 5, the focus was on propositions which disputed whether activity X took place or an alternative activity Y took place. These studies provided new insights in the characteristic fingermark patterns that result from performing certain activities with the use of knifes, pillowcases and letters. Further studies into other objects of interest or other activities would provide fundamental knowledge on the occurrence of fingermark traces under certain activities. However, in these studies, the presence or absence of fingermarks from other (possible uknown) donors was not taken into account. For the application of evaluating fingermarks given activity level propositions in practice, it would be of great value to evaluate case examples using propositions in which the occurence of activity X with the object of interest is accepted, to incorporate the probability of the presence or absence of fingermarks from other donors in the evaluation. This implies conducting experiments focusing on the impact of using an object of interest by multiple donors, both for wearing gloves or bare handed, taking source level evaluations into account. Can we make a distinction between two donors of which one used the object of interest for a daily activity and the other used the object of interest for the activity that is related to the crime?

In this dissertation, we have commented only on the situation in which the defense provides an alternative explanation for the findings. In practice, the cooperation by the defense is limited due to the right to remain silent or due to a strategic point of view to provide a statement after the results of the analysis are known [9]. According to guidelines provided by the ENFSI (European Network of Forensic Science Institutes) [18], the forensic scientists has three options in this situation: he may propose the most reasonable alternative proposition based on the case circumstances, he may explore a range of explanations for the findings or state that due to the absence of an alternative propositions an evaluation of the findings is considered impossible. If later in the judicial process new propositions are put forward by the defense, a revision of the evaluation of these propositions is required [19].

What are the odds?

Once the activity level propositions are formulated, the relevant variables for the case at hand can be selected and a Bayesian network can be constructed following the framework presented in Chapter 2. However, to be able to use the network for an evaluation of fingermarks given the proposed activity level propositions, probabilities need to be assigned to the constructed network. How can we do this properly?

The preferred method to assign probabilties to a Bayesian network is to perform case specific experiments by simulating the case circumstances of the case, since these probabilities will be most representative for the case at hand [13]. Chapter 3 showed how empirical data from case specific experiments with knives could be used to assign probabilities to the states of a Bayesian network. The study in Chapter 3 is the first published study within the field of fingermark research that focusses on the use of case specific experiments for the evaluation of fingermarks given activity level propositions. For the field of forensic biology, there is a much greater awareness of the importance of conducting this type of experiments and publishing the results to help other scientists assign probabilities for transfer, persistence, prevalence and recovery of DNA (see [20] for an overview of the studies conducted in this field). Sharing data on these topics is considered highly relevant since forensic scientists are confronted with similar types of cases in different jurisdictions [21]. The field of fingermarks would also greatly benefit from these types of studies focusing on the transfer, persistence and recovery of fingermarks, and additionally on factors such as the location or direction of the fingermarks. Conducting this type of studies and publishing the results will broaden the knowledge of the scientific community and will aid in helping other scientist to assigning probabilities in casework, especially since not all forensic laboratories have the possibility to conduct experiments due to resources or time limitations [7].

Besides broadening the pool of knowledge with publishing data on case specific experiments, studies focusing on understanding the variables that influence the interpretation of fingermarks given activity level propositions will also aid the assignment of probabilities to a network. An example of this is the study conducted by Chadwick et al. [22], which provides a better understanding on how certain factors influence the detection of fingermarks, leading to a greater understanding of the mechanisms that are in place when depositing a fingermark. These kind of studies are necessary to be able to better understand the dynamics of fingermarks in relation to activities.

An essential component in studying the variables, and an optimal use of data obtained from case specific experiments is the availability of methods to measure a variable. In Chapter 4 and Chapter 5, we presented such a model to objectively measure the variable location of the fingermarks in relation to activity level propositions. However, there are many more variables that are relevant to consider when analyzing fingermarks given activity level propositions for which no measurement methods are available, although highly desirable. Variables such as the direction of a fingermark, the pressure used during deposition, and the transfer, persistence or the recovery of a fingermark. For example, for the variable transfer, it can be questioned how the states of this variable need to be defined and measured. One could think of the possible states 'good', 'medium' and 'poor' and taking the number of minutiae present in a fingermark as a measurement. However, it can be questioned whether the number of minutiae present in the fingermark is the best representation to measure the variable transfer in relation to activity level propositions, since partial fingermarks or smears may also be informative for the evaluation of transfer given activity level propositions. Probably a combination of using a qualitative scoring system (see for examples [23, 24]) with a quantitative analysis of the marks as proposed in the discussion of Chapter 3 may be a better option. Additional research is needed to expand this concept and to design measurement methods for the other variables, since a clear definition of a variable and an objective method to measure a variable is required before these variables can be studied in case specific experiments.

Whenever no empirical data are available to base the probabilities of a Bayesian network on, the probabilities could be assigned based on the expertise of the forensic scientist [13, 25]. Sources to support their assignment could be a systematic review of case files from similar cases or expert elicitation from multiple experts. However, the ground truth in these cases is generally not known [15]. Nevertheless, in case no hard data is available, these may be valuable resources in order to assign the appropriate probabilities to a Bayesian network. In this dissertation, we did not explore these methods as a source of information to inform the probabilities of a Bayesian network. Further research could show the potential of these sources for the evaluation of fingermarks given activity level propositions.

A final option to assign probabilities to a Bayesian network is the use of sensitivity analyses. With the use of a sensitivity analysis, the sensitivity of the LR to a range of reasonable probability values is tested. A sensitivity analysis is often used in conjunction with the use of published data from case studies to study the robustness of the LR to variations that may be expected when applying the data to the case at hand. Another application of a sensitivity analysis is to investigate which variables (nodes) have the most impact on the evaluation, often used to direct further research [26]. In this dissertation, no sensitivity analyses were carried out since the aim in the presented studies was not to provide the actual weight of evidence. In case a formal evaluation is carried out in casework, a sensitivity analysis is recommended. In case the sensitivity analysis determines that the evaluation is not robust, there may be decided not to report the evaluation given activity level propositions.

Important to note is that in practice, often a combination of empirical data, sensitivity analyses and the expertise of the forensic scientist is used to assign probabilities to a Bayesian network. Although using empirical data is the preferred method, this data will not always be available and collecting new data by performing scientific experiments may not always be possible. And even if there is published data available, this data probably never exactly fits the case circumstances of the case at hand. This means that the data should be considered in light of the current case circumstances by the forensic scientist. Both forms of knowledge, more explicit forms of knowledge by using empirical databases and using more tacit forms of knowledge based on the experience of the forensic scientist, are required in order to address a reliable interpretation of the fingermarks [27].

Reporting the results

After an evaluation of fingermarks given activity level propositions has been carried out, the findings have to be reported in a formal report to be used in court. One aspect which is not addressed in this dissertation is how to report these findings. There are a number of publications that provide guidance on how to structure a report on the evaluation of findings given activity level propositions [15, 28–30]. However, no formal studies are conducted on how an evaluation given activity level propositions can be best reported and how this information is received. For example, there are a few studies published showing various opinions on whether Bayesian networks should be included in the final report or not [30–32]; however, there is no scientific evidence to substantiate the statements. Another relevant issue for a report on the evaluation of fingermarks given activity level propositions might be whether pictures of the object of interest should be included. Further research on how an evaluation of forensic findings given activity level propositions can be best reported and how these reports are received is crucial in order to make sure the results are understood correctly in court. An example of such a study is presented by van Straalen et al. [33].

It all starts at the crime scene...

In this dissertation, the focus was mainly on the evaluation of the fingermarks after the object of interest on which the fingermarks are visualized is secured and transported back to the laboratory. However, the forensic process starts at the crime scene. Already at the crime scene, relevant traces need to be detected and collected to be able to analyze the evidence given activity level propositions.

The forensic process at the crime scene starts with a search for forensic traces. Already in this stage of the investigation, variables such as the location or the direction of fingermarks as presented in Chapter 2 are important to consider. How these variables are nowadays used at the crime scene and how knowledge about these variables may improve the searching strategy deserves further study to optimize the detection and collection process of relevant traces for evaluation given activity level propositions. Furthermore, it is important to already anticipate on possible alternative scenarios at this stage of the investigation, to be able to evaluate the evidence given relevant activity level propositions at a later stage of the process [34]. The field of fingermarks would benefit from a study as carried out by Ton et al. [34], to gain insight in the alternative scenarios brought forward by the defense. These alternative scenarios may than already be taken into account during the crime scene investigation, preventing the loss of important traces.

In case forensic evidence is found at a crime scene, the next step is to determine which traces need to be collected. In case fingermarks are found, the variables presented in Chapter 2 are relevant to determine the crime relatedness of the traces. The use of a decision support system in which these variables are considered may help the forensic experts with the selection of traces which are probably related to the criminal activities that must have occured. In this way, the relevant variables for evaluation of the fingermarks given activity level propositions are incorporated in the decision making process at the crime scene [35, 36].

After the decision that a fingermark needs to be collected at the crime scene, there are two options for the collection: the fingermark is lifted from the surface and the lifted fingermark is sent to the laboratory or the object of interest with the fingermark on it is collected, packaged and transported to the laboratory. In case a fingermark is lifted from the surface, variables such as the location or the direction of a fingermark on the surface are crucial to record if later in the process an evaluation given activity level propositions is desired. In case the complete object of interest is collected for further evaluation at the laboratory, the location, direction and placement of the object of interest at the crime scene are important variables to record. Furthermore, it is important that the forensic process of collection, packaging and transportation does not influence the fingermarks present on the object. Any distortion or removal of fingermarks may greatly influence the interpretation of the fingermarks given activity level propositions. Further research on the influence of this process on fingermarks present on an object of interest is necessary to draw solid conclusions on fingermarks with regards to activity level propositions.

6.5. Strengths and limitations

The studies presented in this dissertation provided us with new insights on how fingermarks may provide information about activities that have taken place, but there are some important limitations that make direct implementation in casework difficult. One obvious drawback is that within forensic science, it is difficult to reconstruct a realistic crime scenario. Although we can think of how crimes may take place to mimic the conducted activities as closely as possible, we will never be able to exactly replicate the real-life situation. It is always a possibility that during the crime, there were relevant circumstances that influenced the occurence of forensic traces, which are not considered or cannot be included during the reconstruction. For example, in the knife experiment conducted in Chapter 3, participants used the knife to stab in a styrofoam plate. Obviously, this is not representative for a human being. Although it is possible to represent a human being more closely by using for example a piece of meat, the possible resistance a human victim will provide in a stabbing incident cannot be simulated. Another example is that it can be expected that a perpetrator will experience high levels of stress when conducting a criminal activity, probably causing more sweat which will influence the probability of transfer. These factors are difficult to replicate and test within a laboratory environment. The difficulty of reconstructing a crime scenario does not only apply to fingermarks, but to forensic traces in general. However, this does not mean that numerical values from experiments conducted under controlled conditions cannot be used for the evaluation of real-life cases. As Biedermann et al. [9] clearly point out, this claim conflicts with scientific practice, in which trials are conducted which reflect not all, but the essential features of a problem at hand. It is important to mimic the situation as closely as possible, and clearly point out the differences with real-life scenarios in the resulting report or publication.

Another limitation of the studies we presented is that we only considered two separate activities in each study, without taking into account any pre- or post-activities or without taking into account the occurrence of successive activities. In real life, the objects are most probably exposed to additional activities that were carried out before or after the criminal activity took place. Further research should point out the influence of these additional activities. However, in order to be able to study the influence of any additional activities, it is very important to study any characteristics of the fingermark patterns resulting from the separate activities. The studies presented in this dissertation function as a starting point for further research on pre- or post-activities to show how robust the presented results are when incorporating combined activities.

The studies presented in this dissertation focused on all sorts of fingermarks, without taking the quality of the mark into account. In Chapter 3, we even used videos to study the area of friction ridge skin that left the fingermark, a source that is normally not used for this purpose in practice. However, we felt that with this first exploration of a new type of evaluation, it was not appropriate to eliminate traces that are not of enough quality for a source level evaluation. In this dissertation, we have shown that smears and incomplete fingermarks also provide information with regards to activity level evaluation, showing that these marks are of value regardless their suitability for a source level evaluation. In case the fingermarks turn out to not be of sufficient quality to determine the source of the fingermark, the source may be determined by analysing the DNA present in the touch traces.

Activity level evaluation is mainly seen as a case-to-case approach in which for every case new networks and new data have to be created. This dissertation proves that there are definitely some generalizations possible. In Chapter 2, we have presented Bayesian networks that can function as basic networks for the evaluation of fingermarks. These networks are meant to be used as general building blocks and can be modified according to specific case circumstances, as we have shown in Chapter 3. Furthermore, the model presented in Chapter 4 to evaluate the location of fingermarks with regards to activity level questions on two dimensional items could be extended to be able to also evaluate three-dimensional items in general. The development of these kind of models is crucial to enable the measurement of a variable in general, i.e. in any case and on any object. Finally, we hope that by publishing more data on case specific experiments in the future, general patterns of transfer, persistence and recovery of fingermarks can be observed, which now remain unnoticed.

6.6. Conclusion

This dissertation was part of the project 'Fingermarks, the source and beyond'. The goal of this project was twofold: to obtain new information from fingermarks besides source level information and to study how this new information can be implemented into the judicial process. The development of new technologies to extract more information from fingermarks was divided into two lines of research, my line of research described in this dissertation in which the focus was on activity level information and the line of research carried out by Ward van Helmond in which the focus was on studying the chemical composition of a fingermark. The final line of research carried out by Elmarije van Straalen focused on the implementation of this new information in the criminal justice system.

Ward van Helmond has shown in his research that the chemical composition of a fingermark contains information about the donor of the trace [37], the time of deposition of a fingermark [38] and exogenous compounds that were touched [39]. Together with the information presented in this dissertation, we have shown that besides source level information, fingermarks provide more information about what has happened, when it happened and by who. In the research of Elmarije van Straalen, information is retrieved on how fingermark professionals make decisions during the forensic process, how fingermark evidence is used in Dutch court proceedings and how forensic conclusions may be interpreted by criminal justice professionals [33]. This research has provided new leads on how the newly derived information can be best implemented in the forensic process.

This dissertation has shown that fingermarks may reveal information about activities. Nowadays, fingermarks are solely used to determine the donor of a trace by studying the features present in papillary lines of a fingermark. Until the start of this project, the necessity of analyzing fingermarks given activity level propositions was not acknowledged. I hope this dissertation will motivate others to re-evaluate the current fingermark workflow and to explore new possibilities in evaluating fingermarks with regards to activity level questions. The three research lines together proved that fingermarks contain a wealth of valuable new information for the criminal justice system. I feel that applying this new information into current practices will help the process of fact-finding in court. However, please keep in mind:

> "*It is a capital mistake to theorize before one has data. Insensibly one begins to twist facts to suit theories, instead of theories to suit facts.*"
>
> Sherlock Holmes[1]

6

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A

Supplementary material Chapter 2

The supplementary files of the networks can be accessed via:
`https://www.sciencedirect.com/science/article/pii/S0379073819303172#sec0195`

B
Supplementary material Chapter 3

The supplementary files of the networks can be accessed via:
https://www.sciencedirect.com/science/article/pii/S037907382100030X

Scenario stabbing

Donor	FM	Hand	Direction	Rotation	Side 1	Side 2	Side 3	Side 4	Back	Blade
Donor 1	Yes	Right	Underhand	Down	P/F	P/F	F	F/T	None	None
Donor 2	Yes	Right	Overhand	Down	F	P	P/F	F	None	None
Donor 3	Yes	Right	Overhand	Up	P	F	F	P	T	None
Donor 4	Yes	Right	Overhand	Down	P	P	F	F/T	P	None
Donor 5	Yes	Right	Overhand	Down	F	P	P/F	F	T	None
Donor 6	Yes	Right	Underhand	Down	P/F/T	P/F	F	F/T	None	None
Donor 7	Yes	Right	Overhand	Down	F	P	P/F	F/T	T	None
Donor 8	Yes	Right	Overhand	Down	P/F	P	P	F/T	T	None
Donor 9	Yes	Right	Overhand	Down	F	P	P	F/T	T	None
Donor 10	Yes	Right	Overhand	Down	F	P	P	F/T	T	None
Donor 11	Yes	Right	Overhand	Down	F	P	P	F/T	None	None
Donor 12	Yes	Right	Overhand	Down	F	P	P	F/T	T	F
Donor 13	Yes	Right	Overhand	Down	F	P	P	F/T	None	None
Donor 14	Yes	Right	Underhand	Down	P	P/F	F	P/F/T	None	None
Donor 15	Yes	Right	Underhand	Down	P/T	P	F	F/T	None	None
Donor 16	Yes	Right	Underhand	Down	P/T	P/F	F	P/F/T	None	None
Donor 17	Yes	Right	Underhand	Down	P	P/F	F	F/T	None	None
Donor 18	Yes	Right	Underhand	Down	P/T	P/F	F	P/F/T	P	None
Donor 19	Yes	Right	Underhand	Up	P	F	F	P/T	P	None
Donor 20	Yes	Right	Underhand	Down	P/T	P/F	F	F	P	None
Donor 21	Yes	Right	Overhand	Down	NA	NA	NA	NA	NA	None
Donor 22	Yes	Right	Overhand	Down	F	P	P	F	T	None
Donor 23	Yes	Right	Underhand	Down	P	P/F	F	F/T	P	None
Donor 24	Yes	Right	Underhand	Down	P/F/T	P/F	F	F/T	P	None

Table B.1: Resulting counts for the scenario stabbing, in which Down = cutting face of knife downwards, Up= cutting face of knife upwards, P= Palm, F=Fingers and T=Thumb.

Scenario cutting food

Donor	FM	Hand	Direction	Rotation	Side 1	Side 2	Side 3	Side 4	Back	Blade
Donor 1	Yes	Right	Underhand	Down	P/F	P/F	F	P/T	P	F
Donor 2	Yes	Right	Underhand	Down	P/F	F	F	P/T	P	F
Donor 3	Yes	Right	Underhand	Down	P/F	P/F	F/T	P/T	P/F	None
Donor 4	Yes	Right	Underhand	Down	P	P/F	F	P/T	None	F
Donor 5	Yes	Right	Underhand	Down	P/F	P/F	F	P/T	P/F	F
Donor 6	Yes	Right	Underhand	Down	P/F	P/F	F	T	P/F	None
Donor 7	Yes	Right	Underhand	Down	P/F	F	F	P/T	P	F
Donor 8	Yes	Right	Underhand	Down	P/F	P/F	F	P/F/T	P/F	F
Donor 9	Yes	Right	Underhand	Down	P/F	P/F	F	P/F/T	P	F
Donor 10	Yes	Right	Underhand	Down	P/F	P/F	F	P/T	P/F	None
Donor 11	Yes	Right	Underhand	Down	P	P/F	F	NA	P	None
Donor 12	Yes	Right	Underhand	Down	P/F/T	F	F	P/T	P/F	None
Donor 13	Yes	Right	Underhand	Down	P/F	F	F	P/T	P/F	None
Donor 14	Yes	Right	Underhand	Down	P/F	F	F	P/T	P/F	None
Donor 15	Yes	Right	Underhand	Down	P/F	F	F	P/T	P/F	F
Donor 16	Yes	Right	Underhand	Down	P/F	P/F	F	P/T	P/F	None
Donor 17	Yes	Right	Underhand	Down	P/F	F	F	P/T	P/F	F
Donor 18	Yes	Right	Underhand	Down	NA	P/F	F/T	P/T	P/F	F
Donor 19	Yes	Right	Underhand	Down	P/F	P/F	F	P/F/T	F	F
Donor 20	Yes	Right	Underhand	Down	P/F	P/F	F	P/T	P	None
Donor 21	Yes	Right	Underhand	Down	P/F	F	F	P/T	NA	None
Donor 22	Yes	Right	Underhand	Down	P/F	P/F	F	P/F/T	P/F	F
Donor 23	Yes	Right	Underhand	Down	P/F/T	P/F	F	P/F/T	P/F	F
Donor 24	Yes	Right	Underhand	Down	P/T	P/F	F	P/F/T	P/F	None

Table B.2: Resulting counts for the scenario cutting food, in which Down = cutting face of knife downwards, P= Palm, F=Fingers and T=Thumb.

S stabbed the victim	True				False			
Marks on handle - stabbing	FM S present		FM S absent		FM S present		FM S absent	
Marks on back - stabbing	FM S present	FM S absent	FM S present	FM S absent	FM S present	FM S absent	FM S present	FM S absent
Marks on blade - stabbing:								
FM S present	0.118	0.091	0.5	0.5	0	0	0	0
FM S absent	0.882	0.909	0.5	0.5	1	1	1	1

Table B.3: Conditional probability table for the node (6) Marks on blade – stabbing in network I.

S cut food with the knife	True				False			
Marks on handle - cutting	FM S present		FM S absent		FM S present		FM S absent	
Marks on back - cutting	FM S present	FM S absent	FM S present	FM S absent	FM S present	FM S absent	FM S present	FM S absent
Marks on blade - cutting:								
FM S present	0.52	0.667	0.5	0.5	0	0	0	0
FM S absent	0.48	0.333	0.5	0.5	1	1	1	1

Table B.4: Conditional probability table for the node (9) Marks on blade – cutting in network I.

2. S stabbed the victim with the knife	True								False
4. Marks on handle - stabbing	P	F	P/F	P/T	F/T	P/F/T	Undetermined	None	...
5. Marks on back - stabbing:									
P	0	0,143	0,077	0,143	0,167	0,25	0,1	0	0
F	0	0,143	0,077	0,143	0,167	0,036	0,1	0	0
T	0	0,143	0,308	0,143	0,167	0,214	0,1	0	0
P/F	0	0,143	0,077	0,143	0,167	0,036	0,1	0	0
P/T	0	0	0,077	0	0	0,036	0,1	0	0
F/T	0	0,143	0,077	0,143	0	0,036	0,1	0	0
P/F/T	0	0	0,077	0	0	0,036	0,1	0	0
Undetermined	0	0,143	0,077	0,143	0,167	0,036	0,2	0	0
None	1	0,143	0,154	0,143	0,167	0,321	0,1	1	1

Table B.5: Conditional probability table for the node (5) Marks on back - stabbing in network II.

3. S cut food with the knife	True								False
7. Marks on handle - cutting	P	F	P/F	P/T	F/T	P/F/T	Undetermined	None	...
8. Marks on back - cutting:									
P	0	0,143	0,111	0,143	0,167	0,188	0,2	0	0
F	0	0,143	0,111	0,143	0,167	0,063	0,1	0	0
T	0	0,143	0,111	0,143	0,167	0,031	0,1	0	0
P/F	0	0,143	0,111	0,143	0,167	0,5	0,1	0	0
P/T	0	0	0,111	0	0	0,031	0,1	0	0
F/T	0	0,143	0,111	0,143	0	0,031	0,1	0	0
P/F/T	0	0	0,111	0	0	0,031	0,1	0	0
Undetermined	0	0,143	0,111	0,143	0,167	0,063	0,1	0	0
None	1	0,143	0,111	0,143	0,167	0,063	0,1	1	1

Table B.6: Conditional probability table for the node (8) Marks on back - cutting in network II.

2. S stabbed the victim with the knife	True																							
4. Marks on handle - stabbing	P	F							P/F									P/T						
5. Marks on back - stabbing	None	P	F	T	P/F	F/T	Undet	None	P	F	T	P/F	P/T	F/T	P/F/T	Undet	None	P	F	T	P/F	F/T	Undet	None
6. Marks on blade - stabbing:																								
P	0	0	0	0	0	0	0	0,111	0	0,143	0,125	0	0	0,2	0	0,143	0,1	0	0,167	0	0	0	0,167	0,111
F	0	0,333	0,25	0,333	0,333	0,333	0,25	0,111	0,2	0,143	0,125	0,2	0,333	0,2	0	0,143	0,1	0,333	0,167	0	0,25	0	0,167	0,111
T	0	0	0,25	0	0	0	0,25	0,111	0,2	0,143	0	0,2	0	0	0	0,143	0,1	0	0,167	0	0,25	0	0,167	0,111
P/F	0	0	0	0	0	0	0	0,111	0	0,143	0,125	0	0	0,2	0	0,143	0,1	0	0,167	0	0	0	0,167	0,111
P/T	0	0	0	0	0	0	0	0,111	0	0	0	0	0	0	0	0	0,1	0	0	0	0	0	0	0,111
F/T	0,333	0	0	0	0	0	0	0,111	0,2	0,143	0	0,2	0	0	0	0,143	0,1	0	0	0	0	0	0	0,111
P/F/T	0,333	0	0	0	0	0	0	0,111	0	0	0	0	0	0	0	0	0,1	0	0	0	0	0	0	0,111
Undet	0,333	0,333	0,25	0,333	0,333	0,333	0,25	0,111	0,2	0,143	0,125	0,2	0,333	0,2	0	0,143	0,1	0,333	0,167	0	0,25	0	0,167	0,111
None	0	0,333	0,25	0,333	0,333	0,333	0,25	0,111	0,2	0,143	0,5	0,2	0,333	0,2	1	0,143	0,2	0,333	0,167	1	0,25	1	0,167	0,111

Table B.7: Part I of the conditional probability table for the node (6) Marks on blade - stabbing in network II.

2. S stabbed the victim with the knife	True																									False
4. Marks on handle - stabbing	F/T						P/F/T									Undet									None	…
5. Marks on back - stabbing	P	F	T	P/F	Undet	None	P	F	T	P/F	P/T	F/T	P/F/T	Undet	None	P	F	T	P/F	P/T	F/T	P/F/T	Undet	None	None	…
6. Marks on blade - stabbing:																										
P	0	0,143	0	0	0,143	0,143	0	0,143	0,1	0	0	0,2	0	0,143	0,059	0	0,143	0,2	0	0	0,2	0	0,125	0,111	0	0
F	0,25	0,143	0,333	0,2	0,143	0,143	0,091		0,2	0,2	0	0,2	0	0,143	0,059	0,2	0,143	0,2	0,2	0,333	0,2	0	0,125	0,111	0	0
T	0,25	0,143	0	0,2	0,143	0,143	0,091	0,143	0	0,2	0	0	0	0,143	0,059	0,2	0,143	0	0,2	0	0	0	0,125	0,111	0	0
P/F	0	0,143	0	0	0,143	0,143	0	0,143	0,1	0	0	0,2	0	0,143	0,059	0	0,143	0,2	0	0	0,2	0	0,125	0,111	0,167	0
P/T	0	0	0	0	0	0,143	0	0	0	0	0	0	0	0	0,059	0	0	0	0	0	0	0	0	0,111	0,167	0
F/T	0	0,143	0	0,2	0,143	0	0,091	0,143	0	0,2	0	0	0	0,143	0,059	0,2	0,143	0	0,2	0	0	0	0,125	0,111	0,167	0
P/F/T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,059	0	0	0	0	0	0	0	0	0,111	0,167	0
Undet	0,25	0,143	0,333	0,2	0,143	0,143	0,091	0,143	0,1	0,2	0	0,2	0	0,143	0,059	0,2	0,143	0,2	0,2	0,333	0,2	0	0,125	0,111	0,167	0
None	0,25	0,143	0,333	0,2	0,143	0,143	0,636	0,143	0,5	0,2	1	0,2	1	0,143	0,529	0,2	0,143	0,2	0,2	0,333	0,2	1	0,25	0,111	0,167	1

Table B.8: Part II of the conditional probability table for the node (6) Marks on blade - stabbing in network II.

3. S cut food with the knife	True																							
7. Marks on handle - cutting	P	F							P/F									P/T						
8. Marks on back - cutting	None	P	F	T	P/F	F/T	Undet	None	P	F	T	P/F	P/T	F/T	P/F/T	Undet	None	P	F	T	P/F	F/T	Undet	None
9. Marks on blade - cutting:																								
P	0	0	0	0	0	0	0	0,111	0	0,143	0,2	0	0	0,2	0	0,143	0,111	0	0,167	0	0	0	0,167	0,111
F	0	0,333	0,25	0,333	0,333	0,333	0,25	0,111	0,167	0,143	0,2	0,2	0,333	0,2	0	0,143	0,111	0,333	0,167	0	0,25	0	0,167	0,111
T	0	0	0,25	0	0	0	0,25	0,111	0,167	0,143	0	0,2	0	0	0	0,143	0,111	0	0,167	0	0,25	0	0,167	0,111
P/F	0	0	0	0	0	0	0	0,111	0	0,143	0,2	0	0	0,2	0	0,143	0,111	0	0,167	0	0	0	0,167	0,111
P/T	0	0	0	0	0	0	0	0,111	0	0	0	0	0	0	0	0	0,111	0	0	0	0	0	0	0,111
F/T	0,333	0	0	0	0	0	0	0,111	0,167	0,143	0	0,2	0	0	0	0,143	0,111	0	0	0	0	0	0	0,111
P/F/T	0,333	0	0	0	0	0	0	0,111	0	0	0	0	0	0	0	0	0,111	0	0	0	0	0	0	0,111
Undet	0,333	0,333	0,25	0,333	0,333	0,333	0,25	0,111	0,167	0,143	0,2	0,2	0,333	0,2	0	0,143	0,111	0,333	0,167	0	0,25	0	0,167	0,111
None	0	0,333	0,25	0,333	0,333	0,333	0,25	0,111	0,333	0,143	0,2	0,2	0,333	0,2	1	0,143	0,111	0,333	0,167	1	0,25	1	0,167	0,111

Table B.9: Part I of the conditional probability table for the node (9) Marks on blade - cutting in network II.

3. S cut food with the knife	True																								False
7. Marks on handle - cutting	F/T						P/F/T									Undet									None	…
8. Marks on back - cutting	P	F	T	P/F	Undet	None	P	F	T	P/F	P/T	F/T	P/F/T	Undet	None	P	F	T	P/F	P/T	F/T	P/F/T	Undet	None	None	…
9. Marks on blade - cutting:																										
P	0	0,143	0	0	0,143	0,143	0	0,125	0,2	0	0	0,2	0	0,125	0,1	0	0,143	0,2	0	0	0,2	0	0,143	0,111	0	0
F	0,25	0,143	0,333	0,2	0,143	0,143	0,5	0,25	0,2	0,889	0	0,2	0	0,125	0,2	0,167	0,143	0,2	0,2	0,333	0,2	0	0,143	0,111	0	0
T	0,25	0,143	0	0,2	0,143	0,143	0,1	0,125	0	0,111	0	0	0	0,125	0,1	0,167	0,143	0	0,2	0	0	0	0,143	0,111	0	0
P/F	0	0,143	0	0	0,143	0,143	0	0,125	0,2	0	0	0,2	0	0,125	0,1	0	0,143	0,2	0	0	0,2	0	0,143	0,111	0,167	0
P/T	0	0	0	0	0	0,143	0	0	0	0	0	0	0	0	0,1	0	0	0	0	0	0	0	0	0,111	0,167	0
F/T	0	0,143	0	0,2	0,143	0	0,1	0,125	0	0,111	0	0	0	0,125	0,1	0,167	0,143	0	0,2	0	0	0	0,143	0,111	0,167	0
P/F/T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,1	0	0	0	0	0	0	0	0	0,111	0,167	0
Undet	0,25	0,143	0,333	0,2	0,143	0,143	0,1	0,125	0,2	0,111	0	0,2	0	0,125	0,1	0,167	0,143	0,2	0,2	0,333	0,2	0	0,143	0,111	0,167	0
None	0,25	0,143	0,333	0,2	0,143	0,143	0,2	0,125	0,2	0,111	1	0,2	1	0,25	0,1	0,333	0,143	0,2	0,2	0,333	0,2	1	0,143	0,111	0,167	1

Table B.10: Part II of the conditional probability table for the node (9) Marks on blade - cutting in network II.

C
Supplementary material Chapter 4

Image processing protocol

1. Duplicate image.
2. Rotate the image such that the opening of the pillowcase points to the left.
3. Adjust the brightness such that the corners of the pillowcase can be observed.
4. Crop the pillowcase with a 60 x 70 cm frame.
5. In case the pillowcase is smaller than the 60 x 70 cm frame due to incorrect stretching of the pillowcase during the photography, use the option transform > distort based on bicubic interpolation. Stretch the picture such that the pillowcase matches the 60 x 70 cm frame.
6. Mask the barcode label on the pillowcase.
   - If there is no paint near the barcode label, we assume the barcode label was placed on a non-paint area as instructed in the protocol. Place a gray rectangle with an RGB value of (20,20,20) and of size equal to the barcode label over the barcode sticker.
   - During the experiment, we observed that on some pillowcases, it was difficult to place the label in a non-paint area. If there is an indication for the presence of paint beneath the label, place a transparent rectangle of 0% of size equal to the barcode label over the barcode sticker. Transparent pixels will later in the process be translated to missing values.
7. In case part of the pillowcase is not photographed due to movement of the camera or skewing of the pillow, mask the area within the 60 x 70cm frame that contains missing data with a transparent layer of 0
8. Save the picture as a JPEG file if there are no transparent areas in the image. Save the picture as a PNG file if there are transparent areas in the image.
9. In case one of the following problems occurs, remove the donor from the dataset.
   - Borders of the pillowcase could not be determined due to movement of the camera or wrong lightning conditions during the image-acquisition process.

- Wrong stretching of pillowcase caused a substantial distortion in the pillowcase.

Segmentation software Lexie

A software tool called Lexie was developed to segment the fingermarks from the images. This segmentation process was performed in separate steps.

Colour extraction

Different areas of the hand left different coloured marks on the pillow. These marks were extracted to three separate images based on the colour vectors and the hue of the pixel values, resulting into three gray scale images. The image intensity ranges were then normalized to the same intensity range to allow the same segmentation settings for each image.

To extract a colour from an image, all pixel values were compared to three predefined colours that defined the fingermarks for the fingers, palm and thumb of the hand. A colour vector $\vec{c}$ is equivalent to the triple red, green and blue value of a pixel. The more the colour vectors of the pixel and of the predefined colour point in the same direction, taking the length of the vector into account, the more a pixel is considered to match the predefined colour. To strengthen the colour extraction, the hue of the pixel and the predefined colours were also compared. The hue value of a pixel ranges between 0 and 360 and it is circular, meaning that a hue of 360 is equal to the hue of 0. If the hue of the pixel compared to the hue of the predefined colour differed more than 120, the colours were considered not equal, resulting in an intensity of 0 for that pixel in the resulting image. If the difference was less then 120, the linear ratio of this difference was defined as the hue-factor.

This extraction process, which extracts an intensity I for each pixel p can be formally defined as:

$$I_{i,p} = 255 \cdot \frac{\vec{c_i} \bullet \vec{c_p}}{|\vec{c_i}|} \cdot H_{i,p} \qquad \text{(C.1)}$$

where i represents fingers, palm or thumb, $\vec{c_i}$ its corresponding predefined colour and $\vec{c_p}$ the color of the pixel p. The hue-factor $H_{i,p}$ is defined as:

$$H_{i,p} = \max\left(\frac{|h_i - h_p| \; mod \; 360 - 180}{120}, 0\right) \qquad \text{(C.2)}$$

where h_i is the hue value of $\vec{c_i}$ and h_p the hue value of $\vec{c_p}$. Applying this for the three predefined colours resulted into three gray scale images with intensity ranging between 0 and 255. Figure C.1(a) shows an example of a pre-processed image, before analysis in Lexie. Lexie extracts the colours as denoted in Figures C.1(b)-C.1(d).

Segmentation

Contours of the fingermarks on pillows were identified using a four-neighbour based region growing segmentation using seed and thresholding [1]. This pixel based segmentation method

[1] S. Kamdi, R.K. Krishna, *Image Segmentation and Region Growing Algorithm*, International Journal of Computer Technology and Electronics Engineering (IJCTEE) **2**, 1 (2012).

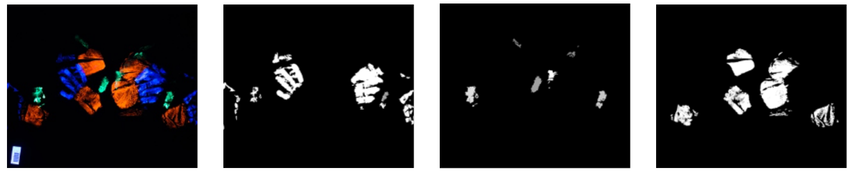

Figure C.1: Visualization of the segmentation steps with Lexie. (a) Original, (b) Fingers, (c) Thumbs, (d) Palms.

uses a threshold for contour definition and a seed for region selection and could be easily applied to the three gray scale images. Pixels with an intensity equal to the seed value or higher are called the seeds. Neighbouring pixels of the seeds were evaluated. If its intensity was above the threshold level, then its neighbouring pixels were also evaluated. This process continued until it reached a pixel that was below the threshold level. This resulted in regions around the seeds, which defined clusters of pixels identified as fingermarks.

Filtering

After segmentation, an additional filter was applied based on the surface of the fingermarks to remove noise elements from the segmentation. Noise elements are small regions that can be caused by drops of paint or dust reflection of the pillow. The surface-threshold allows removing these regions that are not considered fingermarks. Regions with a surface smaller than the surface-threshold were removed from the segmentation.

Partitioning

For the final analysis, the three images are partitioned by a grid, which represents the location areas. For each partition, the number of pixels that are part of a fingermark were counted, which allowed for an analysis of fingermark occurrences per cell. If a fingermark was present that contained more than 5% of the surface of the cell, then the cell was marked as containing a fingermark.

Some pillowcase images contained hidden fingermarks due to skewing of the pillow during photography or when the personal barcode stickers were placed on paint. These areas were marked by changing the transparency of these pixels to 0% during the image pre-processing step. If in a grid cell 5% of the surface of the cell was transparent, then the whole cell was marked with NA.

Settings Lexie

To find the optimal settings of the segmentation software, manually prepared grids were compared to the results of the software for different settings of the threshold, seed and the 250 surface-threshold. Four pillowcase pictures of one donor were manually transformed into a grid by two independent researchers. The manual results were compared, and in consultation, one grid for each pillowcase was found. These final manual grids were compared to the results obtained by Lexie for different settings. The optimal settings were used for the analysis of all images, in which each image is transformed to a 20 x 23 grid with cell size of 3 x 3cm.

Multivariate normality testing

The assumption of multivariate normally distributed data within each class is tested using the Mardia test and QQ plots. The results are shown in Figures C.2, C.3, C.4, C.5 and C.6.

```
   Mardia's Multivariate Normality Test
---------------------------------------
   data : data_smoren_training[c(1, 2)]

   g1p            : 3.159239
   chi.skew       : 48.44167
   p.value.skew   : 7.634565e-10

   g2p            : 12.60609
   z.kurtosis     : 5.522511
   p.value.kurt   : 3.341886e-08

   chi.small.skew : 51.12066
   p.value.small  : 2.106315e-10

   Result          : Data are not multivariate normal.
---------------------------------------
```

Figure C.2: Output R for the Mardia test to assess multivariate normality for the class smothering

```
   Mardia's Multivariate Normality Test
---------------------------------------
   data : data_opmaken_training[c(1, 2)]

   g1p            : 0.9620601
   chi.skew       : 14.75159
   p.value.skew   : 0.005245167

   g2p            : 7.382909
   z.kurtosis     : -0.7398666
   p.value.kurt   : 0.459381

   chi.small.skew : 15.5674
   p.value.small  : 0.003658131

   Result          : Data are not multivariate normal.
---------------------------------------
```

Figure C.3: Output R for the Mardia test to assess multivariate normality for the class changing

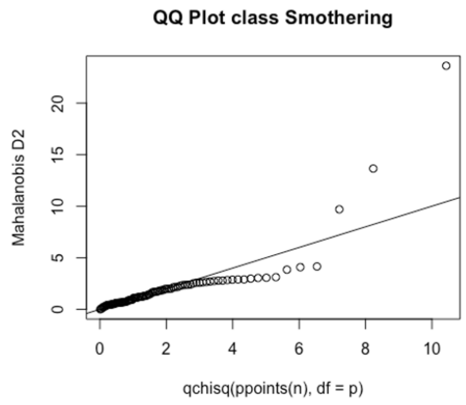

Figure C.4: QQ plot smothering. Used to assess multivariate normality for the class smothering

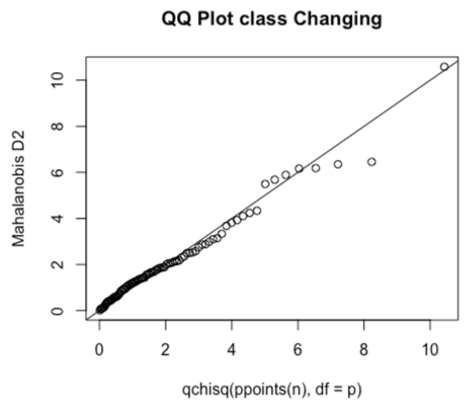

Figure C.5: QQ plot smothering. Used to assess multivariate normality for the class changing

```
Call:
qda(Klasse ~ ., data = alledata[, c(1, 2, 3)])

Prior probabilities of groups:
  changing smothering
       0.5        0.5

Group means:
           Dist_Smoren Dist_Opmaken
changing     0.4746263    0.4690370
smothering   0.3351587    0.4746263
```

Figure C.6: Fitted QDA model.

Acknowledgements

En ineens is het zover: het proefschrift is af! Wat een geweldig avontuur was dit. Dit boekje was er niet geweest zonder de hulp van velen. Ik wil iedereen bedanken die heeft bijgedragen aan het onderzoek, maar in het bijzonder zou ik graag de volgende mensen willen bedanken:

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thousiasme werden zelfs de moeilijkste programmeertermen begrijpelijk. Bas, ik ben super blij dat ik jou betrokken heb bij dit onderzoek want wat heb ik veel van jou geleerd. Samen hebben we de Bayesiaanse netwerken uitgedacht voor dit nieuwe vakgebied, waarbij jij mij altijd stimuleerde om nog even wat beter na te denken over die ene extra pijl of knoop in het netwerk. Hopelijk zullen er in de toekomst nog vele netwerken maar vooral ook andere leuke projecten volgen, nu ook als collega's bij de HvA.

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Curriculum Vitæ

Anouk de Ronde (February 10th 1990, Ede) started her study Applied Mathematics at the University of Utrecht. After obtaining her bachelor degree in 2012, she started her master Forensic Science at the University of Amsterdam. For her master thesis, she conducted research at the Netherlands Forensic Institute, department DNA kinship analysis and investigated the use of complex mixtures for DNA database searches when relatives are present the database. In 2014, she finished her master and started working at the Netherlands Forensic Institute, department DNA kinship analysis on the validation of software that is used for DNA kinship analysis. Next to that, she participated in Project Gerede Twijfel, a project conducting research into alleged miscarriages of justice. In April 2016, she started as a PhD candidate at the Amsterdam University of Applied Sciences, the Netherlands Forensic Institute and VU University.

List of Publications

A. de Ronde, M. van Aken, M. de Puit, and C.J. de Poot, *A study into fingermarks at activity level on pillowcases*, Forensic Science International **295**, (2019).

A. de Ronde, B. Kokshoorn, C.J. de Poot, and M. de Puit, *The evaluation of fingermarks given activity level propositions*, Forensic Science International **302**, (2019).

A. de Ronde, M. van Aken, C.J. de Poot, and M. de Puit, *A study into evaluating the location of fingermarks on letters given activity level propositions*, Forensic Science International **315**, (2020).

A. de Ronde, B. Kokshoorn, M. de Puit, and C.J. de Poot, *Using case specific experiments to evaluate fingermarks on knives given activity level propositions*, Forensic Science International **320**, (2021).