A study into fingermarks at activity level on pillowcases

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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 an alternative activity like '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

[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.

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.

2. Materials and methods experiment

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.

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.

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

[2] https://www.zorgmatras.com/waterdicht-kussen.html

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.

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, 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

[3] For further information on the pressure software, we would like to refer to Arjo Loeve, department Biomechanical Engineering, Delft University of Technology. Email: a.j.loeve@tudelft.nl.

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.

3. Image processing

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 in the supplementary material. 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.

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. 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. Analysis

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

4.1 Classification task

Formally, the purpose of classification is to assign the objects to a class C 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.

4.2 Data pre-processing

For the data pre-processing, the design shown in Figure 1 was used. Since the front and the back of one pillowcase are dependent, we decided to concatenate each two sides of a pillowcase. As a result, we obtained a 20 x 46 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.

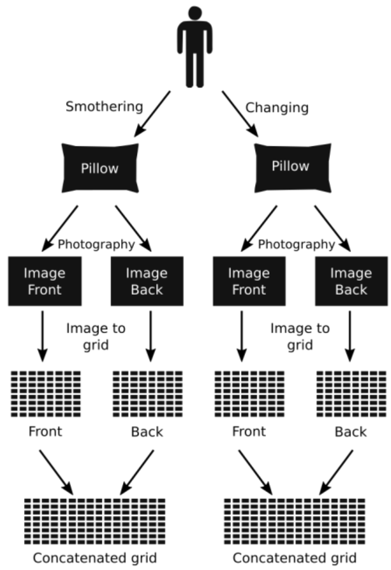


Figure 1: Data construction. The process results in two concatenated rasters per donor.

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.

4.3 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, SI [9]. The value for SI 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 is based on the 2 x 2 contingency table in Table 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		
Vector of pillowcase 1		1	0	
	1	a	b	$a+b$
	0	c	d	$c+d$
		$a+c$	$b+d$	n

Table 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:

$$SI = \frac{a+d}{n} \tag{1}$$

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

$$d = \sqrt{1-SI} \tag{2}$$

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 $\binom{x_1}{x_2}$ 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 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, see James, Witten, Hastie and Tibshirani [12].

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 for 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 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.

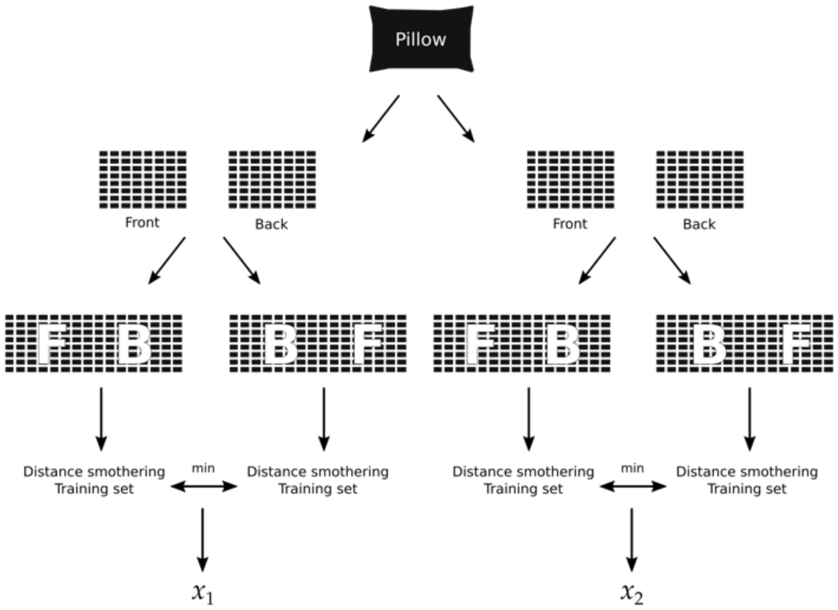


Figure 2: Data construction. Process of testing the test set without using the side of the pillowcase.

4.5 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].

5. Results

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, resulting in 132 donors and 528 images. Table 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 2: Characteristics of the volunteers who participated in the experiment.

5.2 Heat map

Figure 3 and Figure 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.

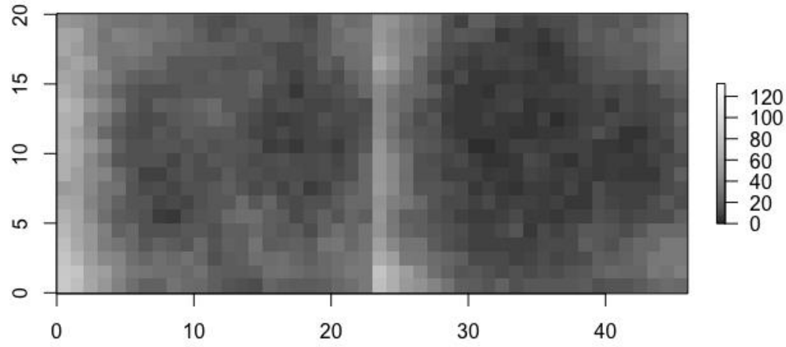


Figure 3: Heat map changing. Shows the heat map of the concatenated pillowcases used under the scenario changing.

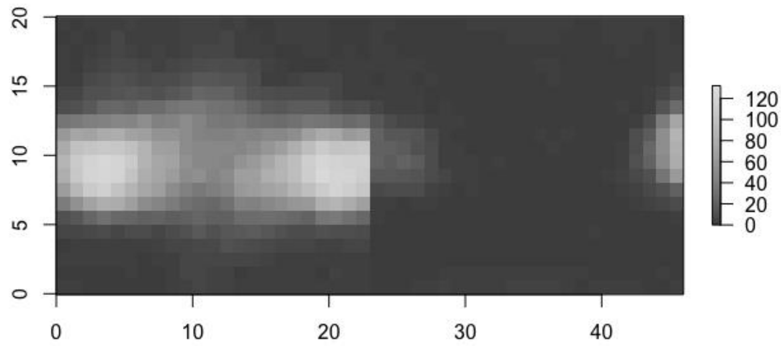


Figure 4: Heat map smothering. Shows the heat map of the concatenated pillowcases used under the scenario smothering.

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 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 to the training set changing are calculated. The resulting feature space is shown in Figure 6. The red dots represent the changing pillowcases, and the blue dots represent the smothering pillowcases. Figure 6 shows that the two classes smothering and changing are distributed into two reasonably separate regions.

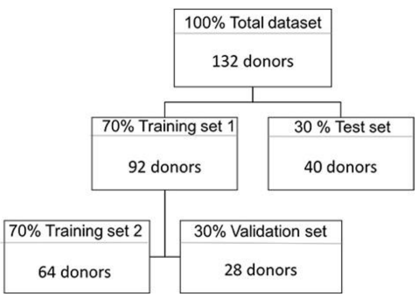


Figure 5: Subsets of total dataset. Division of donors into three separate subsets.

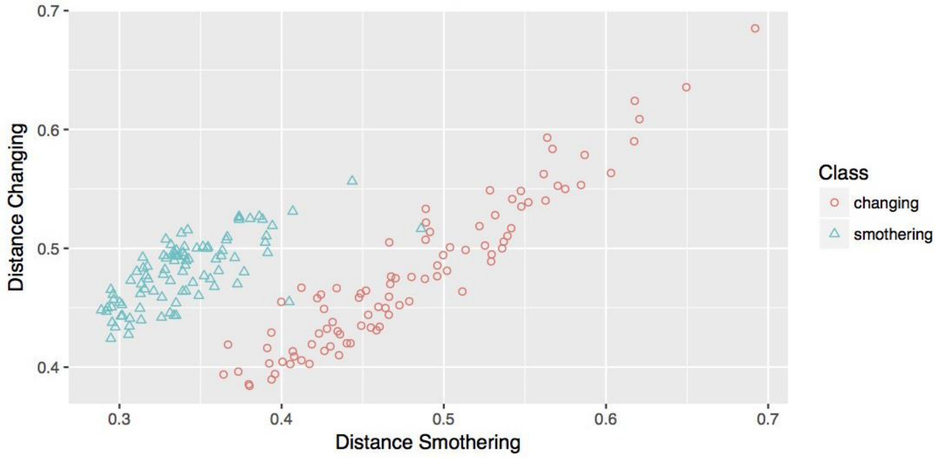


Figure 6: Feature space. Shows the distribution of the pillowcases based on the distance measures.

A QDA classifier assumes the classes to be multivariate normally distributed. We have tested this assumption using the Mardia test and QQ plots (see supplementary material). 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 as supplementary material.

5.4 Evaluation of the model

Table 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 3 shows that the error is a smothering pillowcase that is classified as a changing pillowcase. Within the forensic science community, these false-negative errors are determined to be less problematic than false-positive errors, which are highly undesirable since they involve a higher possibility of an unfair decision-making [17]. 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 3: Confusion matrix for the Test set using the QDA classifier.

5.5 Likelihood ratio

Since classification using QDA is based on the posterior probability $Pr(Y = k|X = \boldsymbol{x})$ for k= (smothering, changing) and $\boldsymbol{x}$ 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 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 [18]. These are the three misclassified smothering pillowcases discussed previously.

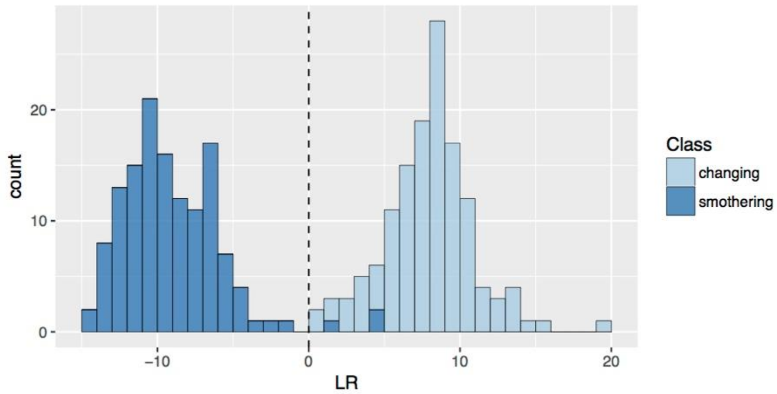


Figure 7: Likelihood ratio distribution. Shows the calculated LR for each pillowcase.

5.6 Side of the pillowcase

Table 4 represents 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**
Smothering	40	0
Changing	25	15

Table 4: Results of predicting the order of concatenation.

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, Bettman, Aarts, Sjerps and Kokshoorn [19]. 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 [20]. 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.

It must be noted that the likelihood ratio values for the pillowcases obtained with our model are very high. These are not the likelihood ratio values we expect to obtain in real cases. However, this research shows a first proof of concept of the possibility to differentiate between two separate activities based on the location of the fingermarks. Further research should demonstrate whether these results are also applicable to casework situations in which pillows are the object of interest.

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 x 70 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].

Supplementary material

1. 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 grey 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.

2. 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.

2.1 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 grey 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:

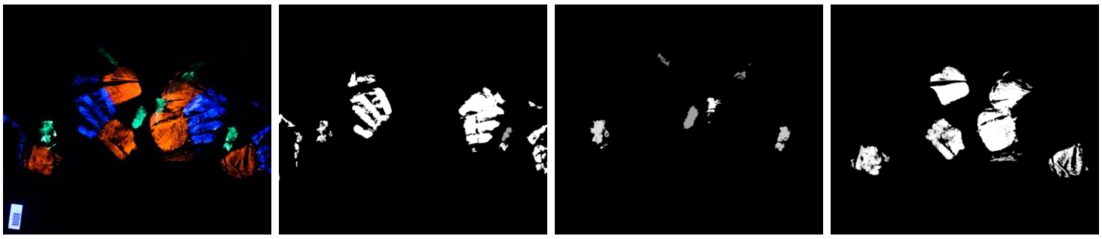
$$I_{i,p} = 255 \cdot \frac{\vec{c}_i \bullet \vec{c}_p}{|\vec{c}_i|} \cdot H_{i,p} \tag{1}$$

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:

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

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 grey scale images with intensity ranging between 0 and

255. Figure S1a shows an example of a pre-processed image, before analysis in Lexie. Lexie extracts the colours as denoted in Figures S1b-S1d.



(a) Original *(b) Fingers* *(c) Thumbs* *(d) Palms*

Figure S1: Image segmentation with Lexie. Visualization of the segmentation steps.

2.2 Segmentation

Contours of the fingermarks on pillows were identified using a four-neighbour based region growing segmentation using seed and thresholding [21]. This pixel based segmentation method uses a threshold for contour definition and a seed for region selection and could be easily applied to the three grey 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.

2.3 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.

2.4 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.

2.5 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.

3. 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 S2, S3, S4, S5 and S6.

```
   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 S2: 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 S3: Output R for the the Mardia test to assess multivariate normality for the class changing.

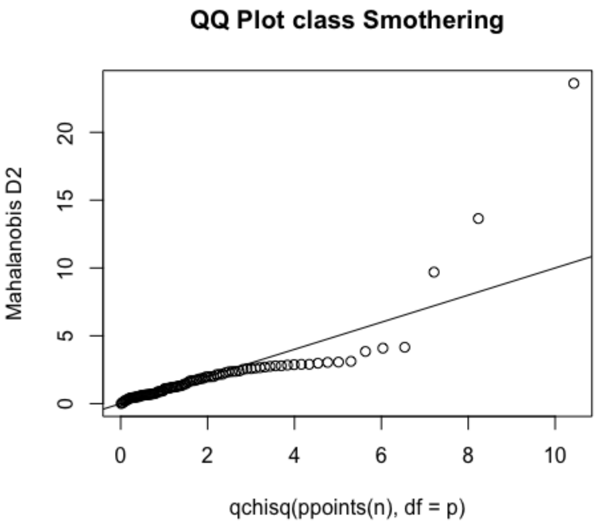


Figure S4: QQ plot smothering. Used to assess multivariate normality for the class smothering.

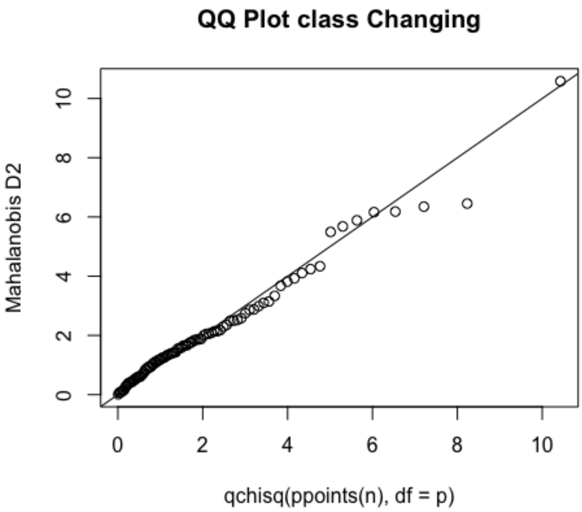


Figure S5: QQ plot changing. Used to assess multivariate normality for the class changing.

```
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 S6: Fitted QDA model.

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