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An automated approach to the classification of impact spatter and cast-off bloodstain patterns

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ABSTRACT

In the forensic discipline of bloodstain pattern analysis, it has been suggested that there is a blurred boundary between characterising the features of a bloodstain pattern and determining the mechanism(s) that led to its deposition. This study proposes that bloodstain pattern classification can become a distinct and logical process by implementing an automated approach. To do this, an automated bloodstain pattern recognition system was developed to enable the distinction of two types of *spatter* bloodstain patterns. First, global pattern features based on common bloodstain pattern properties were extracted from laboratory-generated *impact spatter* and *cast-off* bloodstain patterns. Following this, automated feature selection methods were used to identify the combination of features that best distinguished the two bloodstain pattern types. This eventually led to the training and testing of a Fisher quadratic discriminant classifier using separate subsets of the generated bloodstain patterns. When applied to the training dataset, a 100% classification precision resulted. An independent dataset comprising of bloodstain patterns generated on paint and wallpaper substrates were used to validate the performance of the classifier. An error rate of 2% was obtained when the classifier was applied to these bloodstain patterns. This automated bloodstain pattern recognition system offers considerable promise as an objective classification methodology which up to now, the discipline has lacked. With further refinement, including testing it over a wider range of bloodstain patterns, it could provide valuable quantitative data to support analysts in their task of classifying bloodstain patterns.

1. Introduction

Recognising patterns based on a sizeable body of knowledge that has been stored in the human mind is regarded as a prerequisite to human expert decision-making [1]. Humans have developed sophisticated methods of sensing and interpreting patterns in the environment. Pattern recognition is central to a number of forensic disciplines including bloodstain pattern analysis (BPA). The recognition of bloodstain patterns relies primarily on the identification of the pattern's diagnostic properties and an evaluation of the possible mechanisms by which the pattern was deposited. Together these form the process bloodstain pattern analysts term *pattern classification*. The limitations of pattern classification as currently practiced, are the qualitative nature of determining the properties of the pattern and the subjective judgement required to infer the pattern's causal event [2,3]. It is evident that this process encourages the formation of early mechanistic conclusions about the cause of a pattern before a full set of observations has been made [4]. This problem is exacerbated by the use of standard discipline terminology [5], which is largely mechanism-based. In fact, BPA taxonomies [6,7] form the backbone of bloodstain pattern classification. So the boundary between observation and interpretation or reconstruction can become blurred [8]. A key reason for this and other persisting issues, is the lack of a rigorous and standardised BPA methodology [3,8]. Defining a formal BPA methodology is the subject of ongoing discussion among BPA practitioners [9–11].

Computers offer a wide range of capabilities that can both assist and emulate human decision-making. Pattern recognition has been defined as the study of how computers observe the environment, learn to distinguish patterns of interest and make reasonable decisions about different categories of patterns [12]. Pattern recognition systems can be based on identifying the pre-

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defined class[1] to which an unknown pattern belongs or conversely, classes can be learned based on similarities between patterns. The design of a pattern recognition system generally consists of the following stages: defining pattern classes, data collection, selecting the distinguishing features (referred to as feature selection), specifying classification algorithms and estimating the classification error [14].

Over the years, pattern recognition systems have evolved to become valuable tools that are used to organise or retrieve vast amounts of electronic data [15,16], develop computer-aided diagnosis systems for the detection of disease [17–19] or to identify signature characteristics of fluids [20]. It has become evident, that forensic disciplines are moving away from manual methods of analysis towards more automated computer-based methods of pattern recognition. Examples include the comparison of bullets [21], fingerprints [22], facial features [23], speech [24] and handwriting [25]. Indeed, certain components of pattern recognition systems (e.g. pre-processing, feature extraction and classification) have been successfully employed in bloodstain pattern studies [2,26–30].

However, there does not yet appear to be a comprehensive pattern recognition system designed to distinguish different types of bloodstain patterns based on measurable pattern properties. Therefore, the goal of the present study was to assess the viability of developing an automated pattern recognition system capable of distinguishing bloodstain patterns. To develop the proposed system (see Fig. 1 for an overview), a laboratory-generated reference pattern dataset, consisting of two commonly encountered bloodstain pattern types, was first generated. This included 30 *impact spatter*[2] and 30 *cast off*[3] bloodstain patterns that were specifically digitised for the study. An image-processing methodology was then used to extract features that were representative of common bloodstain pattern properties [26]. Following the identification of the optimal set of features, a classifier[4] was trained and tested with separate groups of patterns from the reference pattern dataset. The performance of the classifier was finally evaluated with an independent dataset consisting of bloodstain patterns that were created on a range of surfaces.

2. Methods

2.1. Generating a reference pattern dataset

2.1.1. Pattern creation

Human blood from one donor was used immediately upon collection to generate the bloodstain patterns used in this study. A total of 60 bloodstain patterns consisting of 30 *impact spatter* and 30 *cast-off* bloodstain patterns were created. As an attempt to represent the variability expected of such patterns, different methods of pattern creation were utilised. For the *impact spatter* patterns, a modified mousetrap [31] was released onto a pool of 2 ml of blood. Alternatively, a similar pool of blood was pipetted onto a wooden block, in the centre of the striking area. A hammer was then used to strike that pool of blood. *Cast-off* bloodstain patterns were created by dipping various objects (finger, hammer and knife) in blood, and swinging them in either an upwards or downwards direction. In both sets of experiments, blood was deposited onto plain white flat walls that were made of Trespa (flat panel based on thermosetting resins; Jongeneel, Den Haag, The Netherlands). All bloodstain patterns were left to dry for 2 hours prior to photography. A separate collection of bloodstain patterns was also sourced (Table 1). These patterns were termed the *independent dataset* and consisted of 22 impact spatter and 20 cast-off bloodstain patterns that were created on either a paint or wallpaper surface. The methods used to create these patterns are reported in Laber et. al. [32].

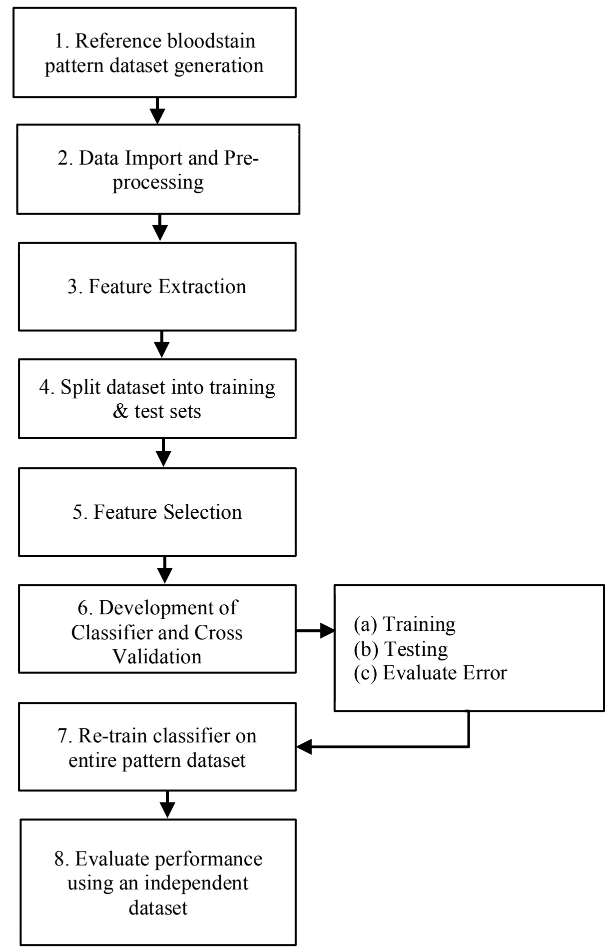

Fig. 1. An overview of the proposed automated bloodstain pattern recognition system.

Table 1
Bloodstain patterns in an independent dataset created by Laber et al. [32].

	Mechanism used to create the pattern	
Substrate	Impact	Cast-off
Paint	12	11
Wallpaper	10	9
TOTAL	22	20

2.1.2. Digitisation and stitching

A customised setup was built to enable the acquisition of high resolution digital images of all bloodstain patterns that were produced in this study (Fig. 2). This setup consisted of a height-adjustable tripod which was secured to a sliding platform. The platform was positioned perpendicular to the Trespa wall at a distance of 210 cm and was able to slide horizontally across the floor at measurable distances. With this setup, a large bloodstain pattern (200 × 100 cm with adhesive scale rulers on all four sides of the pattern) could be captured in the form of four RAW images with 40% overlap. A Nikon 36.3 MP D810 camera with a Nikon AF-S 60 mm macro lens was used to capture the patterns. After photography, the

[1] A class is defined as a set of objects that are recognised as similar within a given context. A class usually has a unique name (class name). The individual objects within a class have a label that refers to this name (class label) [13].
[2] A bloodstain pattern resulting from an object striking liquid blood [5].
[3] A bloodstain pattern resulting from blood drops released from an object due to its motion [5].
[4] A classifier is an algorithmic rule that assigns a class label to any object in a particular object representation [13].

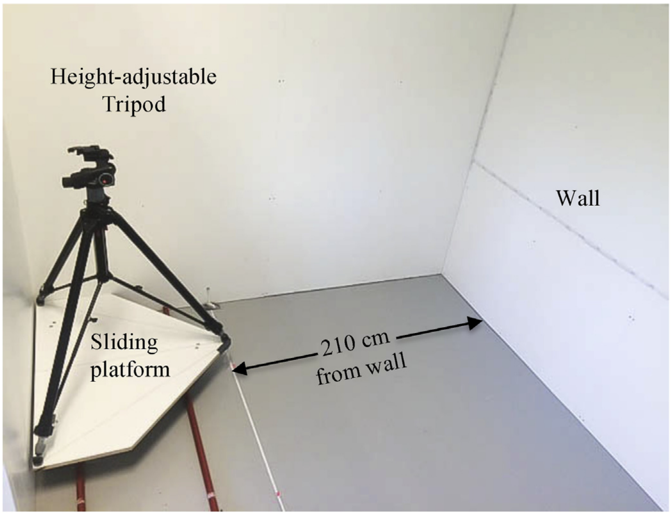

Fig. 2. Camera setup on sliding platform in front of the Trespa wall where bloodstain patterns were created.

four RAW images corresponding to each of the individual 60 bloodstain patterns were combined using the digital stitching process that is available on Adobe Photoshop CS5 v5.1 (Fig. 3). Green circular markers were placed (prior to photography) inside designated regions of overlap, forming landmarks that were used to assist the digital stitching process. The latter process eventually led to the production of single TIFF-format images with a resolution of approximately 6.4 pix/mm as measured by ImageJ 1.48 v software [33]. To be conservative, it was assumed that a minimum of 9 pixels (3×3) was required to resolve an element. This corresponded to an element of approximately 0.22 mm^2 in area or a circular element of approximately 0.5 mm diameter. The entire selection of stitched patterns was termed the *reference pattern dataset.*

2.2. Classifier development

2.2.1. Definitions

Terms used in this study follow those proposed by Ref. [26]. An "*element*" was defined as a contiguous group of pixels in a digitised image of a bloodstained region. A "*pattern*" was designated as a subset of elements that were considered to be related. Both elements and patterns were regarded as having *properties*, for example, shape, or size. The measurable part of a property was termed a "*feature*". *Local features* represented properties of elements and *global features* represented properties of patterns.

2.2.2. Data import and pre-processing

The TIFF-format files that corresponded to the bloodstain patterns in the reference pattern dataset were imported into Matlab R2015b [34] using the built-in image reader, and then individually pre-processed using the automated image-processing methodology outlined in Ref. [26]. Each pattern was pre-processed using the following steps: *background subtraction, element segmentation, morphological operations, labeling and measuring elements, ellipse-fitting* and *feature extraction.*

2.2.3. Feature extraction

Feature extraction[5] was defined as the process of extracting quantitative data representative of properties commonly found in different bloodstain pattern types (e.g. distribution of element shape). In this study, these properties were expressed as features (see Table 1 of the Supplementary Materials) which were extracted using the image-processing methodology outlined in Ref. [26]. This automated methodology provided an objective method of analysis compared to the typical visual assessment of the features of a pattern, by a BPA analyst. Feature extraction was performed on each bloodstain pattern in the reference pattern dataset and eventually led to values corresponding to 11 pattern metrics. A pattern metric was considered to be an overall representation of a global feature in an individual bloodstain pattern. These values were eventually stored in a *feature matrix* (60 rows $\times$ 11 columns) where each row of the matrix (termed a *feature vector*) corresponded to a single bloodstain pattern and each value in the row corresponded to a pattern metric. In pattern recognition literature, the 11-dimensional space occupied by these feature vectors is referred to as the *feature space* [35]. The pattern metrics stored in the feature matrix were:

1. Standard deviation of the tail to body ratio
2. Mean width to length ratio (representing drop impact angle)
3. Mean area of element to area of convex hull ratio (referred to as the 'convex hull ratio')
4. Mean perimeter of inscribed circle to perimeter of element ratio (referred to as 'inscribed circle ratio')
5. Mean element area
6. Standard deviation of element intensity
7. Standard deviation of the gamma angle
8. Standard deviation of the orientation angle
9. Mean Euclidean distance of elliptical elements to a polynomial curve
10. Circularity of the convex hull enclosing all elements of the pattern
11. Element density (i.e. the total number of elements in the pattern divided by the area of the convex hull)

2.2.4. PR dataset generation

Functions from the Matlab pattern recognition toolbox (PRTools) [36] were used to build the bloodstain pattern recognition system. Using this toolbox, a 'PR dataset' variable was constructed. This variable type is defined as a complete representation of all the pattern data that has been stored electronically. The PR dataset consisted of the data in the *feature matrix,* the relevant *class labels* for each pattern (i.e. '*Impact*' or '*Cast-off*') and *feature labels* corresponding to the 11 features that were extracted (i.e. 'Tail to body ratio', 'Impact angle', etc.).

2.2.5. Defining prior probabilities

The probability $P(\omega)$ that a bloodstain pattern belongs to a particular class (ω) is defined as the class prior [13]. In the context of this study, there was an equal probability that a bloodstain pattern in the reference pattern dataset was an *impact spatter* or a *cast-off* bloodstain pattern. On this basis, the class priors were set to 0.5.

2.2.6. Training and test datasets

A *training dataset* is a set of objects that can each be reliably assigned to one class and forms the fundamental basis of building a classifier [13]. A *test dataset* is a set of objects that is only used to test the performance of a classifier, after the classifier has been trained. 24 *impact spatter* and 24 *cast-off* bloodstain patterns were randomly selected to form the training dataset (80%)[6] while the remaining 12 bloodstain patterns formed the test dataset (20%).

[5] In pattern recognition literature, the term 'feature extraction' can also be used to describe algorithms that create new features based on transformations or combinations of the original feature set [35].

[6] The reference dataset was split according to ratios that are prescribed by the Pareto Principle (80:20 ratio).

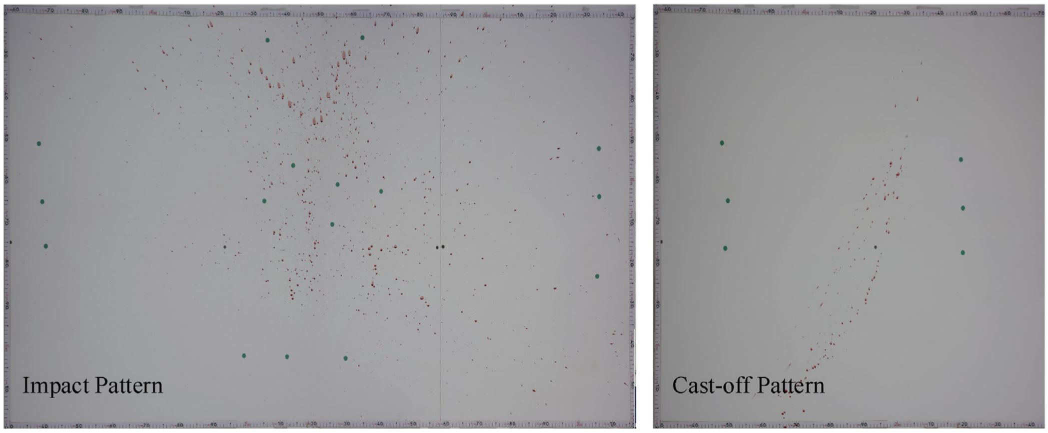

Fig. 3. Example of a stitched impact spatter pattern (left) and a stitched cast-off pattern (right) from the reference pattern dataset. Green circular markers act as landmarks for stitching. Adhesive scale rulers surround the outer extremities of each pattern.

2.2.7. Feature selection and cross validation

Feature selection is defined as a set of algorithms that outputs a subset of features based on the input feature set. The aim of feature selection is to determine those features that perform well under the conditions imposed by a certain classification system [37–39] or to eliminate redundant features [40]. Identifying the ideal feature set can be particularly important when there is a large number of features to select from (e.g. in text classification [15,41]). In this study, sequential backward feature selection (BFS) and sequential forward feature selection (FFS) were performed on the training dataset. With these methods, a *sequential search algorithm* either adds features (FFS) or removes features (BFS) from a candidate subset, while a *criterion function*[7] is evaluated by the search algorithm in order to determine which combination of features best discriminates the classes [42]. 5-fold cross validation[8] was simultaneously performed with feature selection producing estimates of the expected classification error given different combinations of features. In this study, the cross validation error rates resulting from BFS and FFS were evaluated and compared using three different criteria (*sum of the estimated Mahalanobis distance*[9], *inter-intra distance*[10] and *1-nearest-neighbour*[11]). The sequential search algorithm and corresponding criterion function producing the lowest error rate were eventually used to identify the combination of features optimal for the bloodstain pattern classification task.

[7] A criterion function J(X) evaluates the goodness of a subset of features based on the ability of a classifier to discriminate the classes in the feature space represented by this feature set. A larger value of J indicates a better feature subset [42].

[8] Cross validation functions by randomly splitting the training dataset into five folds, and then repeatedly testing the performance of the prospective classifier on each fold when trained on the data in the other four folds [43].

[9] The sum of the estimated Mahalanobis distance criterion function is the sum of the distance between a set of points and a distribution. It measures the separation of two groups of objects.

[10] The inter-intra distance criterion function [39] with k = number of features: $W = \frac{(C_1+C_2)}{2}$ $J = \mathrm{tr}\left(W^{-1} \cdot \mathrm{COV}(\mu)\right)$ Where: C_1 and C_2 is the k-by-k covariance matrix of class 1 and 2 respectively; W is the combined within-class scatter matrix (also k-by-k); μ is a 2-by-k matrix of feature means (one row for either class, one column for each feature); COV(. . .) stands for 'covariance matrix of . . . '; tr(. . .) for the trace function (that is summing the elements on the diagonal of a matrix) and J is the resulting inter-intra distance value.

[11] The 1-nearest-neighbour criterion function involves classifying each data point (in the training data) by assigning it to the true class of its closest neighbour and then checking how many classification errors have been made.

2.2.8. Building the classifier

2.2.8.1. Linear discriminant analysis. This study was based on the assumption that pattern classes can be distinguished by a combination of distinctive properties. This led to the application of a Fisher mapping [44] (also known as Linear Discriminant Analysis; LDA) which assumes that classes are normally distributed, and can be linearly separated by projecting all data onto a linear discriminant subspace[12]. The aim of LDA is to define an orthogonal projection to a line that maximises the distance between the mean of each class while minimising the variance of each class. In this way, such a projection leads to compact and well-separated classes. LDA has been shown to be valuable in face recognition applications [45,46] as it achieves a greater between-class scatter when there are several classes, thereby simplifying classification [45]. Using such a method to increase the separation between classes is of value to BPA because bloodstain patterns can exhibit properties that are common to one or more classes.

2.2.8.2. Quadratic discriminant classifier. A quadratic discriminant classifier (QDC) formed the basis of the bloodstain pattern recognition system. A QDC assumes that each pattern class follows a normal distribution and establishes a decision boundary that maximises the Mahalanobis distance between each class mean. Classification is thus performed by measuring the Mahalanobis distance of an input pattern to the mean of each class [47]. The input pattern is then assigned a class label based on the shortest Mahalanobis distance to a particular class mean. In order to implement this classifier, the Fisher mapping and QDC classifier were combined and trained together with the training dataset. Following this, the trained Fisher QDC was tested with the test dataset. The original class labels were obtained for both training and test datasets and compared with the predicted class labels produced for each dataset. The estimated classification error of the Fisher QDC classifier is reported where relevant.

2.2.8.3. Evaluation of classifier performance. The Fisher QDC classifier was finally trained on the entire reference pattern dataset (i.e. a total of 60 patterns) resulting in a fully trained Fisher QDC (herein referred to as the *trained classifier*). To evaluate the performance of the trained classifier on bloodstain patterns that were not used in its

[12] Variances among groups are assumed to be the same. (i.e. homogeneity of covariance).

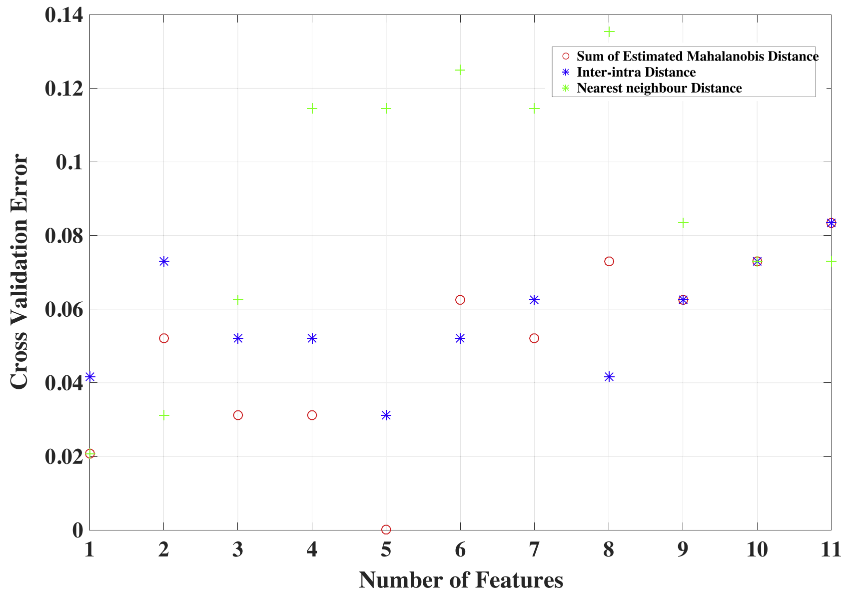

Fig. 4. Cross validation with forward feature selection using three different criteria. Each successive feature is selected by maximising the criterion (J) (red circle = sum of the estimated Mahalanobis distance, blue star = Inter-intra distance, green cross = Nearest neighbour distance). (For interpretation of the references to colour in the text, the reader is referred to the web version of this article.)

development, the *independent dataset* (Table 1) was used as an input to the trained Fisher QDC. For each pattern in the independent dataset, feature extraction was conducted, resulting in data that were stored in a feature matrix. The trained classifier was then used to predict the class labels corresponding to each bloodstain pattern in the independent dataset. The resulting classification precision and posterior probabilities were calculated.

3. Results

3.1. Feature extraction

Values corresponding to each of the 11 pattern metrics were obtained. The range of values observed for each feature and pattern type is shown in Table 2 of the Supplementary Materials.

3.2. Feature selection

Forward (FFS) and Backward (BFS) feature selection was conducted with cross validation in order to identify the optimal feature set and estimate the classification error that could arise from different combinations of features. Error rates were assessed with three different criteria. Fig. 4 with Table 2 shows the cross validation error rates that were obtained after features were sequentially added after each iteration (FFS). These results were similar to those obtained with BFS. Overall, BFS and FFS showed that the optimum number of features was between 4 and 5. On the basis of these results, five features were chosen for the classifier. These features were *mean area, circularity of the convex hull, mean inscribed circle ratio, mean convex hull ratio* and *mean Euclidean distance.* Scatter plots showing the mean area plotted against each of the remaining four features are shown in Figs. 5–8. Note that the training and test datasets used after feature selection comprised only of values corresponding to these five features.

3.3. Building a classifier

3.3.1. Linear discriminant analysis

A Fisher mapping was applied to the training dataset resulting in the projection of these data onto a line (Fig. 9). It is evident that a linear combination of features enabled the separation of the two spatter pattern classes.

3.3.2. Quadratic discriminant classifier (QDC)

The trained Fisher QDC established a decision boundary (Fig. 10), indicating the position of separation between the *impact spatter* and *cast-off* bloodstain pattern classes. When the test dataset was tested by the Fisher QDC, the results demonstrated that the Fisher QDC could accurately predict all of the class labels corresponding to each bloodstain pattern. The position of the decision boundary, however, highlighted a region of overlap between both peaks (Fig. 10) suggesting the potential for erroneous classification.

3.3.3. Evaluation of classifier performance

The trained classifier accurately predicted the class labels of 23 bloodstain patterns in the independent dataset which were deposited on a smooth painted surface and 17 bloodstain patterns deposited on a wallpaper surface. One cast-off bloodstain pattern deposited on wallpaper was erroneously classified, representing an overall error rate of 2%. The remaining cast-off bloodstain pattern (Cast-off Test 12) had insufficient elements for which all features could be measured and was therefore unable to be automatically classified. The predicted class labels and posterior probabilities that were generated for each pattern in the independent dataset are given in Table 3 of the Supplementary Materials.

4. Discussion

Sequential feature selection and linear discriminant analysis demonstrated that five pattern features were sufficient to distinguish the *impact spatter* and *cast-off* patterns in the reference pattern dataset in this study. Of these features, mean element area was the most effective. Impact spatter patterns often exhibit a high proportion of small elements resulting from the production of very small droplets as contact is made between the impacting object and a blood pool. In this study, this could have been accentuated by the nature of the flat surfaces of the mouse trap used to create the spatter.

Table 2
Features sequentially added (FFS) with the Mahalanobis distance, Inter-intra distance and Nearest-neighbour distance criteria.

Criterion: 1)Mahalanobis distance 2) Inter-intra distance		Criterion: 3) 1-Nearest neighbour distance	
Number of features	Feature added	Number of features	Feature added
1	Area	1	Area
2	Circularity of the convex hull	2	Tail to body ratio
3	Inscribed circle ratio	3	Intensity
4	Convex hull ratio	4	Width to length ratio
5	Mean Euclidean distance	5	Convex hull ratio
6	Tail to body ratio	6	Inscribed circle ratio
7	Intensity	7	Orientation
8	Density	8	Density
9	Gamma angle	9	Circularity of the convex hull
10	Orientation	10	Gamma angle
11	Width to length ratio	11	Mean Euclidean distance

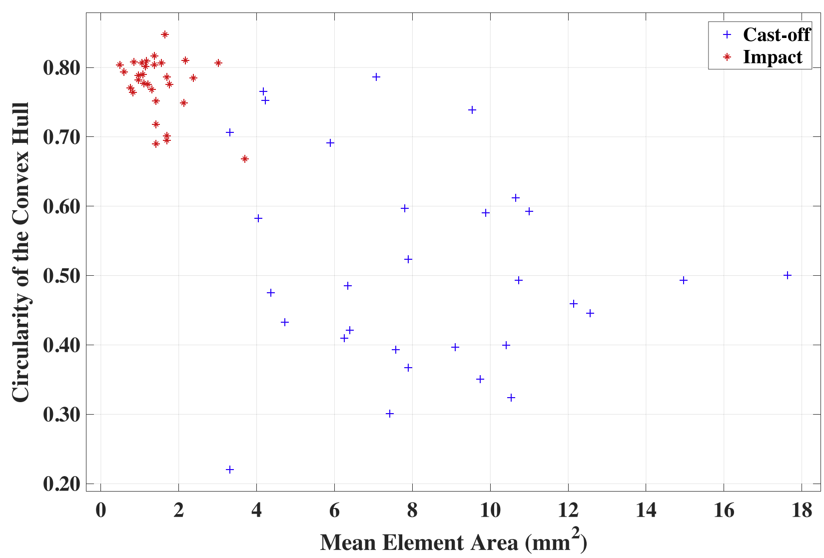

Fig. 5. Mean element area versus circularity of the convex hull.

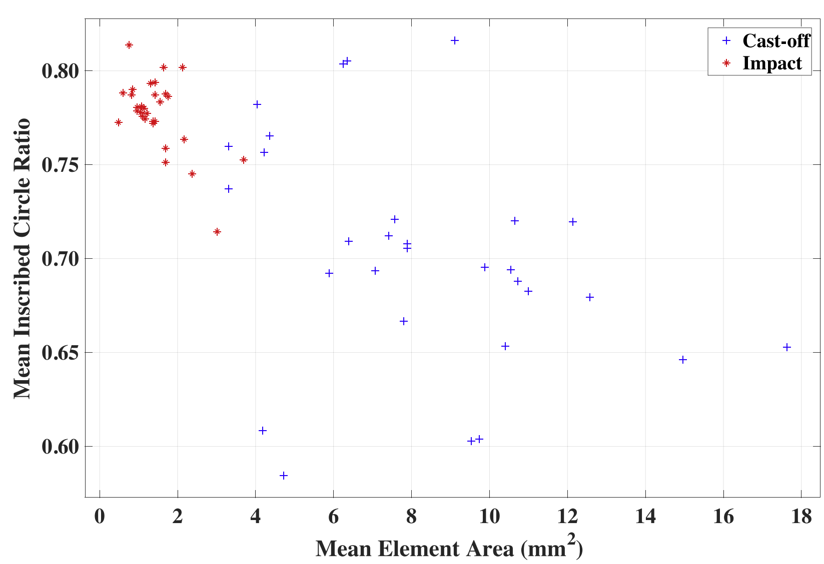

Fig. 6. Mean element area versus mean inscribed circle ratio.

The remaining four diagnostic features that emerged were circularity of the convex hull of the pattern, mean Euclidean distance, mean element convex hull ratio and mean element inscribed circle ratio. These features added some additional discriminating value to the classifier.

The circularity of the convex hull is a measure of the overall distribution of elements in a pattern. The circularity of the convex hull for the cast-off patterns in the reference pattern dataset was generally lower than that of the impact patterns (Fig. 5). This reflects the fact that elements in cast-off patterns tend to be

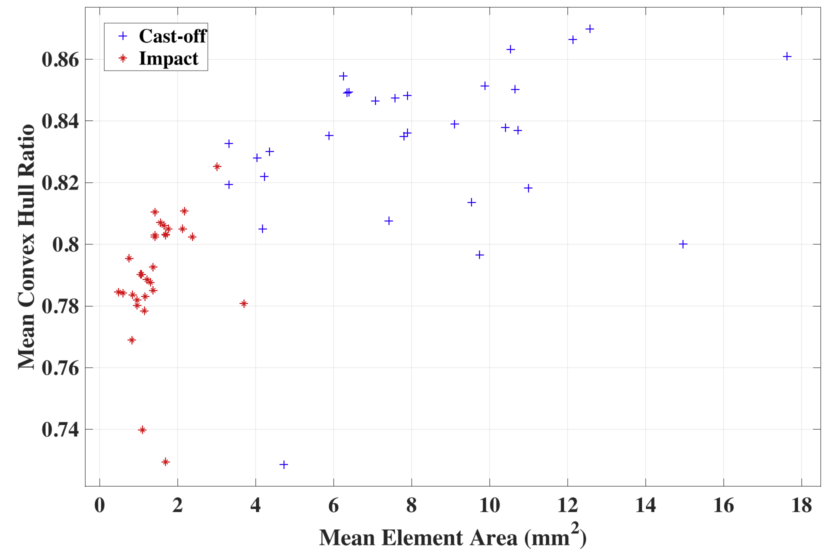

Fig. 7. Mean element area versus mean convex hull ratio.

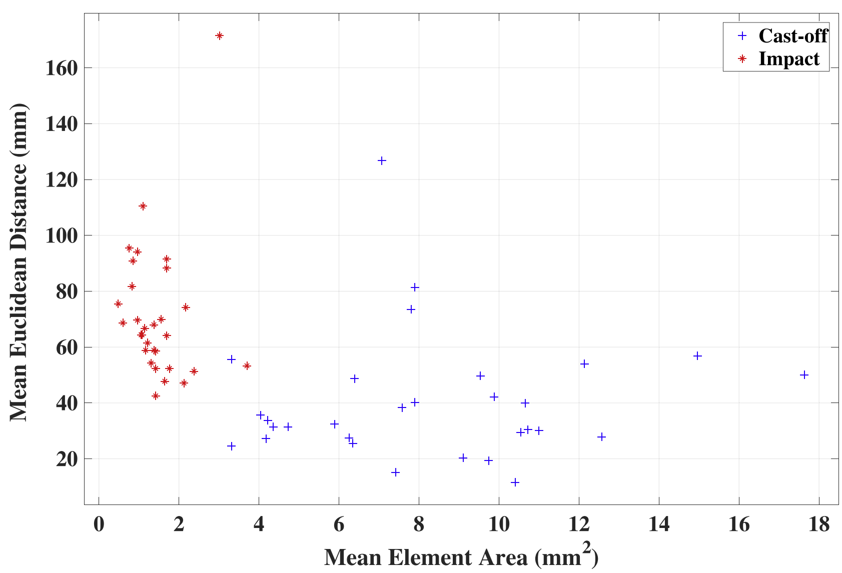

Fig. 8. Mean element area versus mean Euclidean distance.

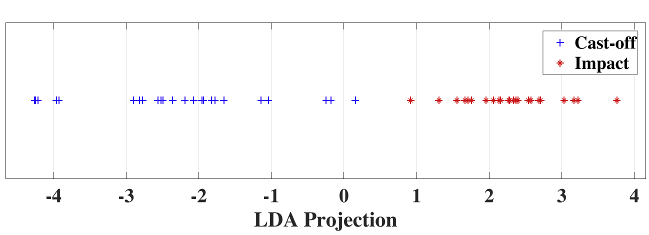

Fig. 9. Mapping of the training dataset to a linear discriminant subspace showing that cast-off (blue crosses) and impact spatter (red stars) patterns could be separated into classes. (For interpretation of the references to colour in the text, the reader is referred to the web version of this article.)

distributed in an elongated manner compared to a more circular distribution of elements that are radially-dispersed in impact patterns (Fig. 11). Because of the high variability in the manner in which impact patterns can be created, more work is required to see if this feature proves diagnostically useful over a wider range of impact mechanisms. Much will depend on whether the entire extent of the pattern can be visualised and captured.

The overall shape of a bloodstain pattern was also measured by the mean Euclidean distance of elliptical elements to a least-squares fitted polynomial curve. This feature was based on the tendency in some patterns for elements to be distributed in a straight or curved line. For the impact patterns in the reference pattern dataset, the mean Euclidean distance was generally higher than that of the cast-off patterns (Fig. 8). This suggests that elliptical elements in impact spatter patterns tend to be distributed further away from a fitted polynomial curve than in cast-off patterns. This is consistent with current classification methods which recognise that in cast-off events, individual blood droplets are ejected over time and at various points along the trajectory of the object being swung. This tends to lead to a linear or curvilinear distribution of elements [6]. In the case of impact spatter patterns, however, elements tend to be more widely dispersed, with elliptical elements generally located at the periphery of the pattern [6].

The element convex hull ratio is a measure of the regularity of the element boundary or margin. For elements with smooth boundaries, this ratio is expected to be close to 1. For the impact patterns in the reference pattern dataset, this ratio was generally lower than for the

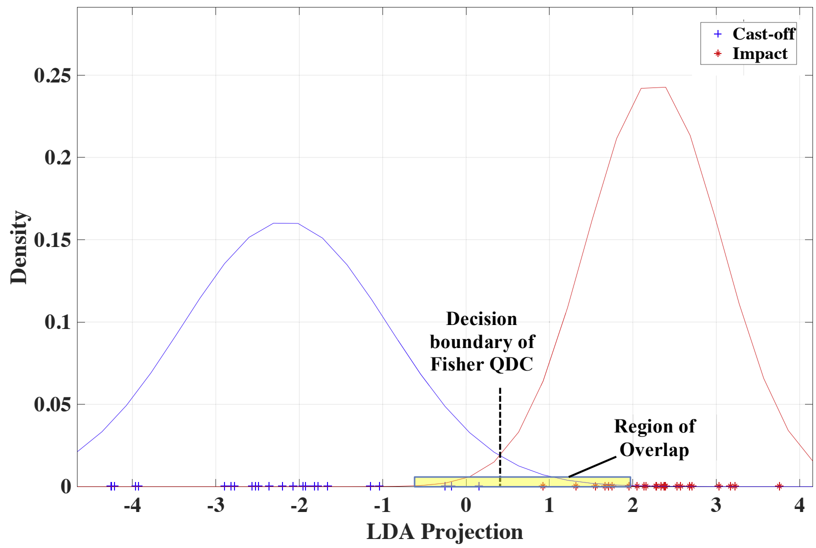

Fig. 10. Fisher mapping with quadratic classification of the training dataset (cast-off = blue crosses, impact spatter = red stars). Decision boundary of Fisher QDC shown (dotted line) and region of overlap between classes (yellow rectangle). (For interpretation of the references to colour in the text, the reader is referred to the web version of this article.)

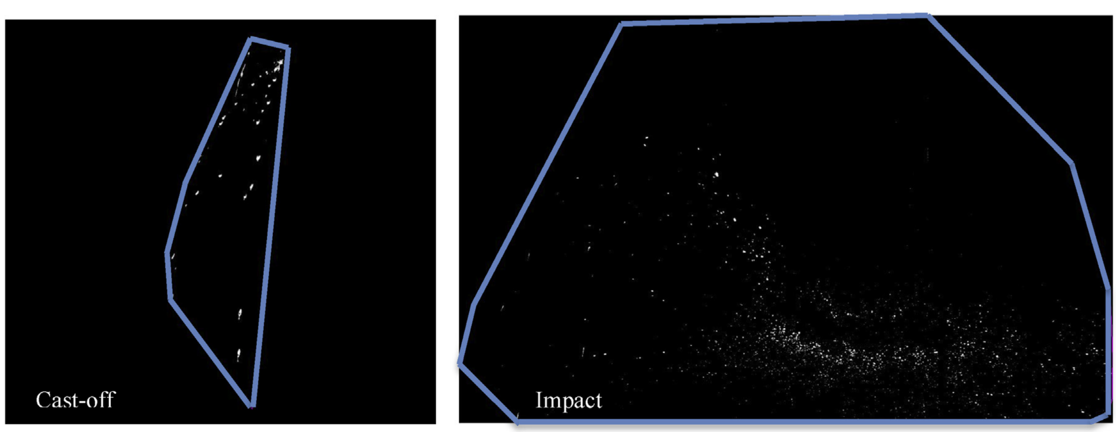

Fig. 11. The convex hull of cast-off pattern 16 (circularity = 0.4) and impact pattern 29 (circularity = 0.8).

cast-off patterns (Fig. 7), reflecting the fact that the elements in the impact patterns had margins that were on average more irregular than those of cast-off patterns. Impact events typically produce an array of liquid sheets and ligaments and other amorphous shaped volumes of liquid, many of which eventually equilibrate into spherical drops. Depending on their progress towards equilibrium, these volumes of liquid can form irregularly-shaped elements. Furthermore, because drops can arrive at the target surface over a period of time, there is the potential for one drop to land on another, causing micro-splashing and the formation of an element with a less regular margin. The production of cast-off drops is typically more uniform with drops forming at regular intervals from the break-up of ligament strands. This may account for the presence of elements with more regular margins.

The element inscribed circle ratio is a measure of the circularity of an element and a secondary measure of the regularity of the element margin. This measure compares the shape of the body of an element to a circle that is fitted within the boundaries of that element. Values closer to one indicate that elements are nearly circular in shape. For the impact patterns in this study, this ratio was generally higher than for the cast-off patterns (Fig. 6). Impact patterns often feature a large number of small near-circular elements in proximity to the location of the impact and these were evident in many of the impact patterns in this study (Fig. 12). The

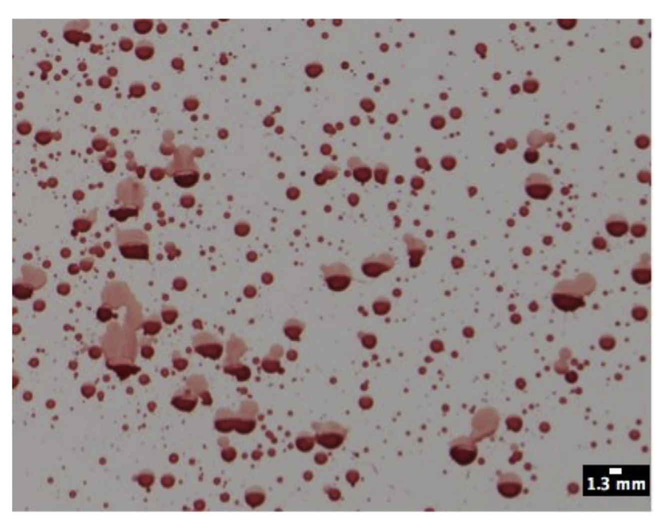

Fig. 12. Presence of near circular elements in an impact spatter pattern from the reference pattern dataset.

Table 3
Values of the five selected features for the erroneously classified cast-off bloodstain patterns in the reference pattern dataset.

Erroneous pattern ID	Mean area (mm^2)	Circularity of the convex hull	Mean inscribed circle ratio	Mean convex hull ratio	Mean Euclidean distance (mm)
Cast-off Test 11	1.95	0.0651	0.649	0.485	0.000007

presence of these elements may account for the differences in mean element inscribed circle ratio observed for these two pattern types.

The trained classifier misclassified one of the cast-off bloodstain patterns in the independent pattern dataset (Fig. 1 of the Supplementary Materials). A closer look at this pattern and its corresponding properties provides some useful insights (Table 3). The misclassification of this pattern appears to be primarily the result of the mean element area. This was lower ($<2\,mm^2$) than those of all the cast-off patterns in the reference pattern dataset but within the range exhibited by the impact patterns. This is likely to be the result of differences in the method used to create these cast-off patterns.

Pattern linearity is a major diagnostic feature used by bloodstain pattern analysts to identify cast-off bloodstain patterns. However the influence of the mean Euclidean distance metric on the classification of the pattern was apparently insufficient to lead to a correct classification. Other measures of linearity may need to be found to improve the performance of the classifier in identifying cast-off patterns.

The reference pattern dataset in this study only contained a small sample of bloodstain patterns and featured a limited range of methods used to create the patterns. The classifier was trained on bloodstain patterns captured on a smooth Trespa wall surface. It is likely that classification accuracy will improve given a reference pattern dataset with patterns deposited on a wider range of surface types. Features such as element convex hull ratio and inscribed circle ratio may be among those sensitive to substrate characteristics.

5. Conclusion

The automated classifier developed in this study demonstrates the viability of a quantitative methodology for bloodstain pattern classification. The findings showed that the combination of a small number of measurable features was capable of distinguishing two pattern types with a high level of accuracy.

In addition to the improved objectivity such a method could bring, it is likely that human factors such as contextual bias, that are known to affect BPA analyses, could be mitigated.

With the development of suitable imaging techniques, the classifier has the potential to be used at a crime scene to provide a trained analyst with objective pattern data to complement his/her expert judgement. For example, objective measures of pattern characteristics such as element size, shape and distribution could be obtained and presented in discriminating combinations. Data to help analysts take decisions regarding the need for further analysis (e.g. estimating the region of origin[13] if an *impact spatter pattern* is suspected) should also be forthcoming.

To be useful for bloodstain pattern analysts, however, the study needs to be extended to a wider range of bloodstain pattern types created in a variety of ways on different surfaces and presented in three dimensions. A wider pool of features may be required to achieve success in discriminating other patterns, particularly those that are known to share pattern characteristics.

[13] The three-dimensional location from which spatter originated [6].

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.forsciint.2018.05.019.

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