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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.

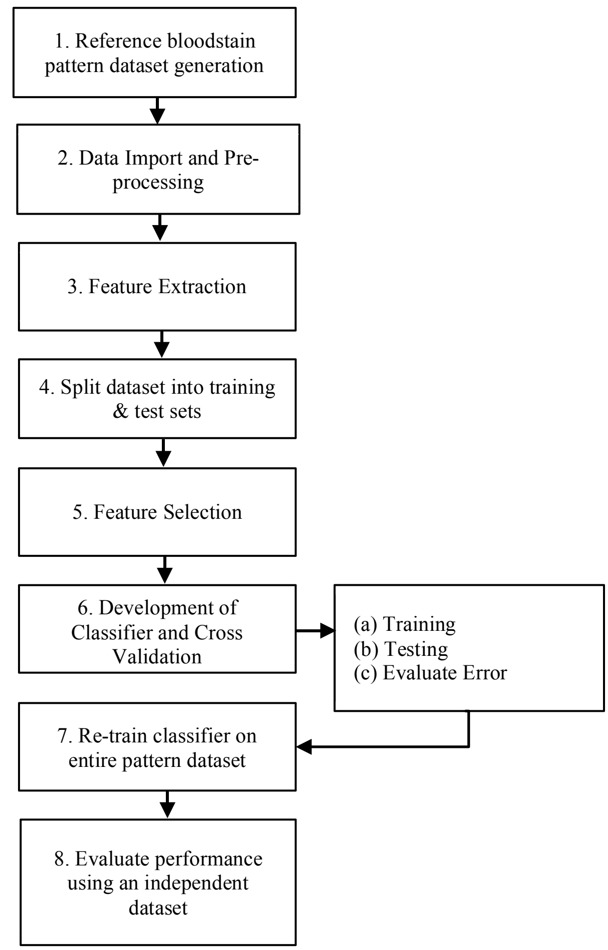

Fig. 1. An overview of the proposed automated bloodstain pattern recognition system.

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].

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].