Forensic Science International 277 (2017) 122–132

Contents lists available at ScienceDirect

Forensic Science International

journal homepage: www.elsevier.com/locate/forsciint

An image-processing methodology for extracting bloodstain pattern features

Ravishka M. Arthur[a,*], Philomena J. Humburg[b], Jerry Hoogenboom[c], Martin Baiker[c], Michael C. Taylor[d], Karla G. de Bruin[c]

[a] School of Chemical Sciences, The University of Auckland, Private Bag 92019, Auckland 1142, New Zealand
[b] School of Geographical and Earth Sciences, University of Glasgow, University Avenue, G12 8QQ Glasgow, Scotland, United Kingdom
[c] Netherlands Forensic Institute, P.O. Box 24044, 2490 AA The Hague, Netherlands
[d] Institute of Environmental Science and Research Ltd. (ESR), Christchurch Science Centre, P.O. Box 29-181, Christchurch 8041, New Zealand

ARTICLE INFO

Article history:
Received 23 February 2017
Received in revised form 2 May 2017
Accepted 26 May 2017
Available online 3 June 2017

Keywords:
Bloodstain Pattern Analysis
Image-processing
Forensic science
Classification
Local features
Global features

ABSTRACT

There is a growing trend in forensic science to develop methods to make forensic pattern comparison tasks more objective. This has generally involved the application of suitable image-processing methods to provide numerical data for identification or comparison. This paper outlines a unique image-processing methodology that can be utilised by analysts to generate reliable pattern data that will assist them in forming objective conclusions about a pattern. A range of features were defined and extracted from a laboratory-generated impact spatter pattern. These features were based in part on bloodstain properties commonly used in the analysis of spatter bloodstain patterns. The values of these features were consistent with properties reported qualitatively for such patterns. The image-processing method developed shows considerable promise as a way to establish measurable discriminating pattern criteria that are lacking in current bloodstain pattern taxonomies.

1. Introduction

Bloodstain Pattern Analysis (BPA) is the forensic discipline concerned with the evaluation and interpretation of bloodstain patterns found at crime scenes. The analysis of bloodstain patterns can provide investigators with useful information about the events that led up to a crime. BPA is conducted primarily through direct crime scene evaluation or careful analysis of photographs of the scene [1–3]. Central to BPA is the classification process. Bloodstain pattern classification is the process of assigning a pattern to one or more categories based on the features of the pattern and their relationship with the blood shedding event(s) that gave rise to them. This can assist the reconstruction of the crime.

Bloodstain patterns tend to be classified and interpreted simultaneously in line with current BPA terminology [4] that is used by BPA analysts when documenting bloodstain patterns. This terminology is predominantly mechanism-focused [5] and can lead to analysts associating a cause before a full set of observations has been made about the pattern [5,6]. It is well known that some bloodletting events can give rise to bloodstain patterns that exhibit similar or indistinguishable features [1,2]. This can create challenges for the analyst in distinguishing the underlying mechanism(s) and can subsequently lead to conflicts in pattern classification between analysts, e.g. [7,8]. There are also limitations for the analyst if the pattern cannot be compared to measurable pattern criteria. The lack of objective, measurable pattern criteria has been identified as one drawback of current bloodstain pattern taxonomies [5].

In recent years, research effort has been directed towards the perceived need to make forensic pattern comparison tasks more objective. This has generally involved the application of suitable image-processing methods to provide numerical data for identification or comparison. Digital image-processing methods have been used to enhance video-surveillance data [9,10], for latent fingerprint recognition [11,12] and for shoeprint comparisons [13–15]. In most cases, the aim has been to improve the resolution of images, enhance human interpretation in the presence of compounding backgrounds or to detect images that have been tampered with [10]. Techniques such as spectral processing and noise reduction filtering have been applied to bloodstain images to improve and enhance the contrast between bloodstains and dark substrates [16]. Cropping, gray-scale conversion and resampling

* Corresponding author.
E-mail address: ravishkaa@gmail.com (R.M. Arthur).

http://dx.doi.org/10.1016/j.forsciint.2017.05.022
0379-0738/

have been used in processing infrared images of bloodstains on clothing substrates [17]. Finally, binarisation [18–20], contrast stretching [21], edge detection [22] contour extraction [23] and object recognition [24] have also been used as part of early processing steps in studies involving bloodstain pattern images. In the current study, a variety of image-processing steps were integrated to form a detailed image-processing methodology for the analysis of digital images of bloodstain patterns to enable the direct measurement of well-known pattern features.

The goal of this methodology is to enable analysts to generate reliable pattern data that will assist them in reaching objective conclusions about the pattern. This method aims to mimic the feature extraction process that is often subconsciously carried out by a BPA analyst. Furthermore, this approach may be effective in dealing with the often 'noisy' data inherent in many bloodstain patterns, arising from scene artefacts and substrate effects. It also enables the extraction of quantitative data from bloodstain patterns thereby providing a direct source of measurable pattern criteria for bloodstain pattern taxonomies. This methodology was produced within the context of an impact spatter pattern, However, with the future capability of including the analysis of other bloodstain pattern types, this methodology lends itself to an automated system that distinguishes different bloodstain patterns.

To develop and illustrate the application of the method, a laboratory-generated impact spatter bloodstain pattern was used. Spatter bloodstain patterns comprise of stains resulting from blood droplets that have been put into free flight. One type of spatter pattern is an impact pattern. This is defined as a "bloodstain pattern that results from an object striking liquid blood" [4]. Under ideal conditions, impact patterns can exhibit a number of characteristic and reproducible properties that can be identified by a trained BPA analyst. These properties formed the basis of the choice of features that were extracted from the pattern used in this study. For example, impact spatter stains can appear to radiate outwards with a progressive change in the shape and size towards the periphery of the overall pattern. In addition to this, impact patterns often have many elliptical-shaped stains (Fig. 1). These stains are generally composed of an elliptical parent body connected (sometimes only partially) to a tail [1,2]. The tail in combination with its elliptical body can be used to make inferences about the directionality of the droplet at the time of impact and used further to estimate an *area of convergence*[1] [1,25]. An ellipse can be used to model the key parameters of spatter stains, such as its shape and orientation. The lengths of the major and minor axes are used in BPA calculations to estimate the droplet impact angle (α) as shown in Eq. (1) [26]. The angle between the major axis and a vertical reference line, referred to as the gamma angle (γ), can be used to estimate the approximate trajectory of the blood droplet that resulted in the stain [1,2]. It is important to note that fitting an ellipse to a bloodstain is generally conducted using only the elliptical parent body of the stain. The tail, if present, is not taken into account. It can be challenging to estimate the boundary between the body and tail of an elliptical stain, potentially leading to imprecise ellipse-fitting and the underestimation of the impact angle [27]. Finally, a dynamic spattering event can lead to differences in the colour and the distribution of stains. For instance, smaller stains can appear lighter in colour due to a smaller volume of blood that is present.

$$\alpha = \arc \sin \frac{\text{Minor Axis Length}}{\text{Major Axis Length}} \quad (1)$$

[1] The area containing the intersections generated by lines drawn through the major axes of individual stains that indicates in two dimensions the location of the blood source [4].

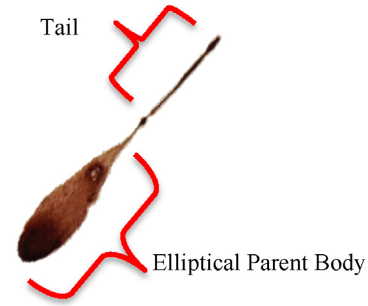

Fig. 1. Elliptical bloodstain with parent body and tail components.

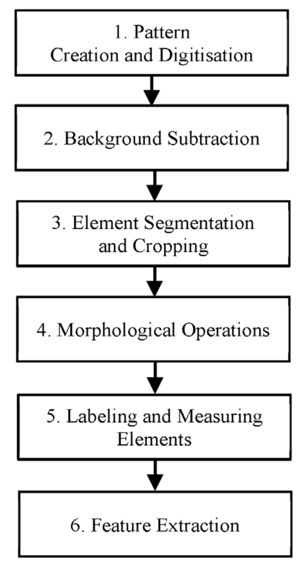

Fig. 2. Overview of the image-processing methodology.

In this paper, a novel image-processing methodology is presented for the analysis of digital bloodstain pattern images. This method comprised a sequence of image-processing steps leading to the automated extraction of diagnostic features (Fig. 2). These features were based in part on the well-known properties of impact spatter bloodstain patterns that are used by analysts.

2. General methods

2.1. Definitions

The use of well-defined nomenclature is of paramount importance to the discipline of BPA. In this study, the following definitions have been used. An *element* is defined as a contiguous group of pixels in a digitised image of a bloodstained region. A *pattern* is defined as some subset of elements that are considered to be related. Both elements and patterns are regarded as having properties, for example, shape, lightness or size (Table 1). Where these properties are measurable, they are termed *features*. In an image-processing context, a feature generally refers to a global property of an image such as the average gray level, or a local property of an image such as circles, lines or elements composing a textured region [28]. In this study, measurable properties of elements were termed *local features* and measurable properties of patterns were termed *global features* (Table 1).