Bloodstain Pattern Analysis
A New Challenge for Computational Intelligence Community

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Abstract: Bloodstain pattern analysis (BPA) is a forensic discipline that plays a key role in tracing events which caused a bloodshed at a crime scene. Indeed, BPA supports worldwide investigation agencies (US FBI, Italian Carabinieri and so on) in interpreting the morphology and distribution of bloodspots at a crime scene in order to enable a potentially complete reconstruction of the dynamics of the act of violence with a consequent identification of potential suspects for that crime. However, in spite of its importance, this forensic discipline is still based on completely manual approaches, making the analysis of a crime scene long, tedious and potentially imperfect. This position paper is aimed at proving that computational intelligence methodologies can be efficiently integrated with image processing techniques to support forensic investigators in increasing their performance in examining bloodstains, both in terms of time and accuracy of analysis. A preliminary study involving the application of fuzzy clustering has been carried out in order to validate our opinion and stimulate computational intelligence community to face this new challenge towards a formal definition of *Forensic Intelligence*.

1 INTRODUCTION

Bloody crimes among strangers, acquaintances or family members are becoming more and more frequent in our society, resulting in a growing sense of fear in the population with related sociological and relational issues. In order to address this increasing wave of violence, worldwide investigation agencies are making strong efforts to improve their abilities in analysing crime scenes through sophisticated scientific methods aimed at efficiently solving complex cases and acting as a deterrent to violent crimes. In this novel investigation scenario, Bloodstain Pattern Analysis (BPA) is assuming a crucial role thanks to its potential skills in identifying precious clues useful for the complete reconstruction of the dynamics of acts of violence. Precisely, BPA is a forensic investigation discipline that deals with the analysis of morphology and distribution of bloodstains at crime scene. Its principal aim is to shed light on various forensic matters including reconstruction of events, differential diagnosis of homicide/suicide/accident and identifying areas with high likelihood of offender movements for taking DNA samples. The first systematic study of bloodstains was published in 1895 by Eduard Piotrowski from the University of Krakow. In this study, entitled "On the formation, form, direction and spreading of blood stains resulting from blunt trauma at the head" at the University of Vienna, Piotrowski covered the corner of a room with sheets of white paper and observed and documented the bloodstains that resulted from beating rabbits to death (Brodbeck, 2012). Since that time, BPA has become an established analytical technique in forensic investigations and the International Association of Bloodstain Pattern Analysts (IABPA) was founded to support the continuing development of the discipline. However, in spite of its importance, BPA is still based on a fully manual approach, making the analysis of a crime scene long, tedious and potentially imperfect. Indeed,

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by following the current BPA guidelines, investigators use their experience to manually identify blood spatter patterns and perform geometrical measures to locate the *point of origin*, i.e. the spatial location where the identified bloodstains has been originated. The collection of points of origin is then used by investigators to try to determine the full dynamics of events at the crime scene.

This position paper is aimed at proving that computational intelligence methodologies can be efficiently integrated with image processing techniques to support forensic investigators in increasing their performance in applying BPA, both in terms of time and accuracy of analysis. In particular, image processing techniques can be used to capture pictures from a crime scene, remove noise, register that pictures and extract the collection of features that computational intelligence methods can efficiently analyse to make BPA faster and more precise than current manual approaches. A preliminary study involving the application of fuzzy clustering for reproducing the well-known *string method* has been carried out in order to validate our opinion and stimulate computational intelligence community to face this new challenge towards a formal definition of *Forensic Intelligence*.

2 BLOODSTAIN PATTERN ANALYSIS

Blood is one of the most significant and frequently encountered types of physical evidence associated with a violent crime (James et al., 2005). Consequently, forensic investigators use a formal methodology, the BPA, to assesses bloodstains left at crime scenes by using an approach based on visual pattern recognition (Brodbeck, 2012). Thanks to this visual approach, BPA investigators analyse the size, shape, and distribution of bloodstains resulting from bloodshed events in order to determine the types of activities and mechanisms that produced them. In particular, BPA may provide several types of information to forensic investigators as, for example (James et al., 2005): 1) areas of convergence and origin of the bloodstains, 2) type and direction of impact that produced bloodstains or spatter, 3) mechanisms by which spatter patterns were produced, 4) assistance with the understanding of how bloodstains were deposited onto items of evidence, 5) possible position of victim, assailant, or objects at the scene during bloodshed, 6) possible movement and direction of victim, assailant, or objects at the scene after bloodshed, support or contradiction of statements given by accused and/or witnesses, 7) additional criteria for estimation of *post-mortem* interval. Moreover, BPA is used to shed light on other forensic matters such as differential diagnosis of homicide/suicide/accident and identifying areas with high likelihood of offender movements for taking DNA samples.

BPA activities are based on a bloodstain classification from S. James, P. Kish and P. Sutton (James et al., 2005) which divides bloodstains into three categories, *passive/gravity*, *spatter* and *altered* based on stain physical features of size, shape, location, concentration, and distribution (Brodbeck, 2012). In detail, passive category describes bloodstain patterns that are formed under the influence of gravity. This group includes contact stains, which result from contact between two surfaces, of which at least one has blood on it. Contact stains often provide information about sequences of movement. Flow patterns, pooling/saturation and drip stains also belong to this category. Spatter category includes spatters that result from active events such as a shot, as well as spatters that are caused by, for example, expiration or cast-off from objects that are swung. Altered category contains all further stain types, such as blood clots and diluted blood that results from the addition of other liquids.

All the BPA analysis depends on the fact that blood is a complex non-Newtonian viscoelastic fluid. For this reason, a drop of blood tends to form into a sphere rather than a teardrop shape when in flight. Ideally, once the sphere lands on a flat surface, the collision flattens the liquid creating an elliptical or circular stain depending on the angle of impact. The angle of impact is the angle at which a blood droplet impacts a surface, measured with respect to a imaginary line perpendicular to that surface. In particular, the more acute the angle of impact, the greater the elongation of the bloodstain as the width decreases and the length increases (James et al., 2005) (see Fig. 1).

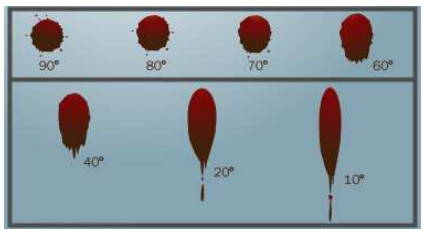


Figure 1: Elongation of bloodstains in terms of the angle of impact[1].

Starting from the aforementioned bloodstain classification and the physical features of blood, BPA an-

[1]http://science.howstuffworks.com/bloodstain-pattern-analysis3.htm

alyst can determine the impact angle of blood on a flat surface by evaluating the shape of the blood spatter stain through trigonometric principles. In detail, the analyst has to locate each spatter and measure its length L (major diameter) and width W (minor diameter) using a scale, a ruler or calipers (see Fig. 2). Then, he or she computes the angle of impact α by using the following formula:

$$\alpha = \arcsin \frac{W}{L} \tag{1}$$

BPA analysis focuses only on primary stains (the stain obtained when the blood drop just touches a surface), however, it is worth noting that the collision is a complex interaction that produces also non-primary spatter patterns caused by displacement, dispersion, and retraction processes. Moreover, target surface absorbency, surface texture, and blood volume are important variable in blood pattern formation and BPA analysts need to adapt their evaluations to these different factors.

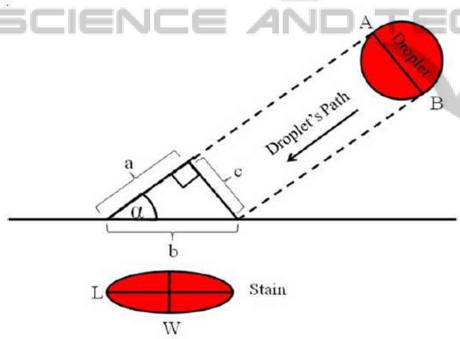


Figure 2: Schematic image (Boonkhong et al., 2010) of the bloodstain from a blood droplet with an impact angle α. In the calculation of α, an analogy is made between line c and b and the width W and length L of the stain.

The consolidated method to determine the point from which the blood originated, named *point of origin*, is known as *string method* (James et al., 2005). The name of this method comes from the way in which forensic experts analyse the bloodstains (see Fig. 3). In particular, once identified a spatter pattern, the analyst attaches elastic strings at the tip of the bloodstains' ellipse and extends them backward, or 180° opposite of their individual directions of travel. The two dimensional point, named *point or area of convergence*, where the strings intersect represents the two-dimensional geographic location of blood source. Determining the area or point of origin combines the two-dimensional area of convergence plus the angle of impact α discussed above for each of the stains belonging to the pattern. In detail, analysts pull elastic strings from the surface according to the angle α. In this way, the angle of impact adds the third dimension to the point of convergence determination, creating a spatial representation of the location of the blood source. This method gives forensic experts an upper bound on the height at which the victim was struck. However, repeating this process for up to hundreds of blood stains takes substantial time and effort (Shen et al., 2006). Moreover, it assumes the identification of a spatter pattern based on forensic experts' knowledge.

Figure 3: Analyst performing the string method (James et al., 2005).

3 COMPUTATIONAL INTELLIGENCE FOR BLOODSTAIN PATTERN ANALYSIS

As highlighted in Section 2, BPA and, in particular the string method, represents a crucial activity in each investigation task related to a violent crime. However, BPA activities could be affected by a set of strong uncertainties due to different factors that can make the overall forensic analysis not significant. Indeed, firstly, a crime scene is inherently imprecise due to high interaction occurring among victim, aggressor and surrounding environment. Moreover, the string method is performed manually by means of imprecise tools and, as a consequence, each step related to this activity adds more and more inaccuracies. In our vision, all this imprecision make BPA an application domain particularly suitable to be addressed by computational intelligence techniques. Indeed, fuzzy reasoning methods could be efficiently used to support pattern recognition activities in BPA in order to analyse the shape of blood spots and compute convergence points and areas, and points of origin of hits.

At the same way, neural networks and other learning approaches could be used to automatically classify bloodstains by taking into account the heuristic classification of bloodstains perfumed by James et al. 2005. Finally, optimisation capabilities provided by evolutionary algorithms could be useful to derive the most suitable path followed by victim and aggressor in a crime scene that is characterised by the presence of an appropriately analysed collection of bloodstains. These are just few examples of application of computational intelligence techniques to BPA but, however, in our opinion a very fruitful research path could start in this scenario, making BPA as the mainstream application of Forensic Intelligence area. Fig. 4 shows our idea for a general template of a system architecture where image processing and computational intelligence techniques are integrated in forensic investigation activities to implement intelligent BPA tools.

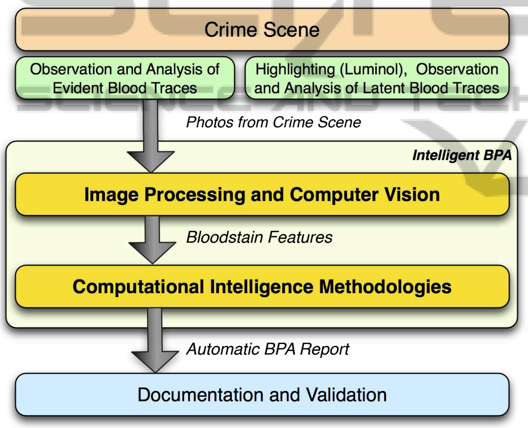


Figure 4: Overview of the proposed generic architecture for intelligent BPA.

In order to validate our vision, an embryonic intelligent tool for BPA is introduced. This tool uses a computer vision algorithm for image rectification and the fuzzy C-Means clustering algorithm extended with the silhouette approach for identifying different bloodstain patterns present in a given image and, for each pattern, computes the convergence area and point of origin. In other words, the proposed tool represents the first attempt to make the BPA string method completely automatic and unrelated to imprecise tools and tasks.

3.1 An Intelligent Tool for BPA

This section presents an embryonic tool designed to perform the string method in an automatic, fast and precise way. The proposed system performs a sequence of tasks summarized in Fig. 5. In particular,

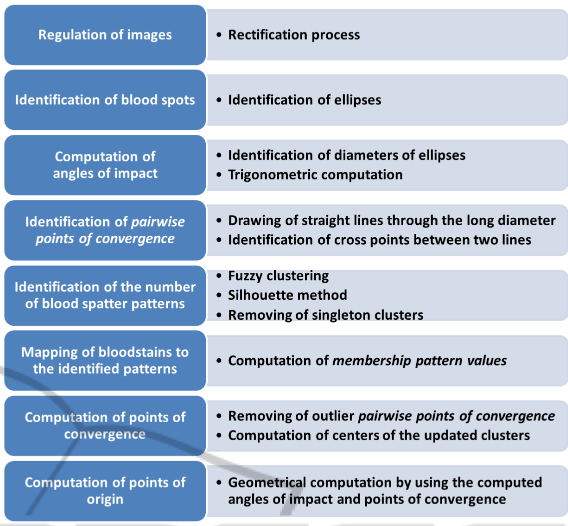
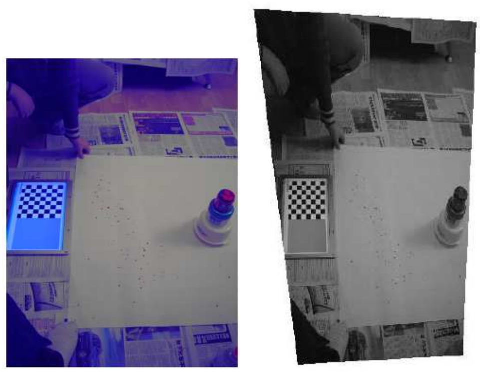


Figure 5: Overview of tasks performed by the proposed system.

the first task consists in registering all photographs of a crime scene to a common virtual image.

Indeed, in order perform an opportune analysis, the bloodstain images should satisfy the following constraint: to be photographed with the image plane parallel to the surface where the bloodstains impacted. Unfortunately, often the captured images at a crime scene have not this feature. Therefore, the proposed system performs a rectification process through image processing techniques, as described in (Shen et al., 2006), in order to obtain to look as if the camera had been looking down at the crime scene from directly above. Fig. 6 presents an example of a photograph subject to the rectification process.



(a) Original photo (b) Relative rectified photo

Figure 6: Example of the rectification phase.

After the rectification phase, the proposed system executes a direct least squares fitting method (Fitzgibbon et al., 1999) in order to identify blood spots in a photograph. Fig. 7 shows a photograph where the

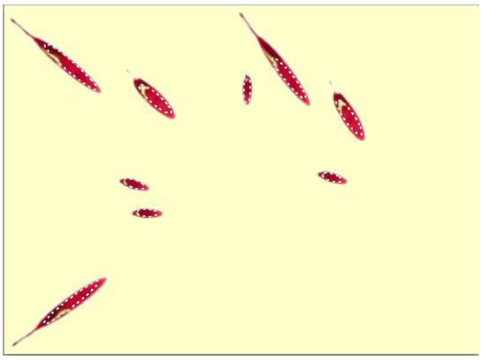


Figure 7: Image where the dotted lines show the identified blood spots.

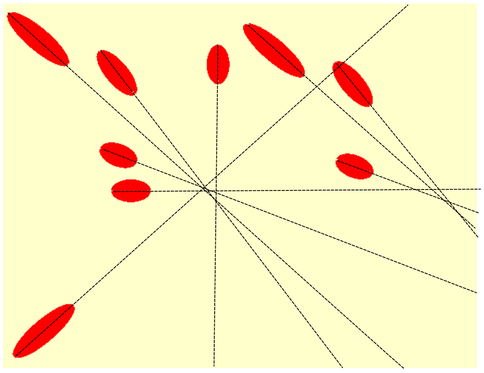


Figure 8: Pairwise points of convergence computation.

dotted lines are the identified blood spots.

Successively, the proposed system computes the major and minor diameters of each identified blood spot. In detail, for the i^{th} identified blood spot, the proposed method computes two points $p_1^i = (x_1^i, y_1^i)$ and $p_2^i = (x_2^i, y_2^i)$ corresponding to the farthest points on the ellipse related to the bloodstain under analysis and two points $p_3^i = (x_3^i, y_3^i)$ and $p_4^i = (x_4^i, y_4^i)$ corresponding to the nearest points. The distance between the points p_1^i and p_2^i represents the length of the i^{th} blood stain L^i, whereas, the distance between the points p_3^i and p_4^i represents the width W^i. L^i and W^i are used to compute the angle of impact of the i^{th} bloodstain as described in section 2.

Then, the successive step performed by the proposed approach is to build a dataset useful for the identification of the number of blood spatter patterns in a photograph. Firstly, the proposed system uses the conventional formula to compute a straight line through the farthest two points p_1^i and p_2^i for each blood i:

$$\frac{y - y_1^i}{y_2^i - y_1^i} = \frac{x - x_1^i}{x_2^i - x_1^i}$$

Then, the system gathers a set of points F, where each point represents the cross between two drawn lines. These points, denoted as *pairwise points of convergence*, represent the blood source for the involved couple of bloodstains. Fig. 8 shows the building of the collection of the pairwise points of convergence.

Once a photograph has been registered and a set of pairwise points of convergence has been collected, the system exploits a fuzzy clustering procedure extended with silhouette method (Rousseeuw, 1987) to identify the number of the blood spatter patterns present in the photograph and the relative points of convergence. These points of convergence together with the previously computed values of angles of impact will be used to compute the points of origin. In detail, the proposed system computes the number of blood spatter patterns as the number of obtained clusters and the relative points of convergence as the center of the correspondent cluster. The exploited fuzzy clustering procedure is the well-known Fuzzy C-Means (Bezdek, 1981) which allows one piece of data to belong to two or more clusters with a different membership degree. This feature is useful in an environment characterized by high uncertainty such as a crime scene. The dataset in input of the Fuzzy C-Means are the set of pairwise points of convergence. The most opportune number of clusters in which dataset must be divided is computed by using the silhouette method. In detail, the proposed approach performs the Fuzzy C-Means M times by using each time a different number of clusters $k \in \{1, 2, \ldots, M\}$, where M is the number of bloodstains in the photograph. This upper bound for value k is chosen by reflecting that there is at least a bloodstain for each spatter pattern, and as a consequence, the number of spatter patterns can not be greater than the number of bloodstains. Then, the best number of clusters is chosen by applying the silhouette method, i.e., it is chosen the number of clusters which allows to obtain the greatest value of the overall average silhouette width (Rousseeuw, 1987). By considering our example, Fig. 9 shows the values of the overall average silhouette widths for each tested $k = 2, \ldots, 9$. As shown, in our example, the best number of clusters in which dataset should be divided is 3. Fig. 10 shows the output of the fuzzy clustering procedure for $k = 3$.

However, as highlighted in (Rousseeuw, 1987), one should not merely accept a high overall average silhouette width, but also look the output of clustering procedure in order to observe the presence of outlier values. Indeed, when a cluster contains only a point of the input dataset, it is very probable that this point is an outlier. Therefore, the proposed system removes singleton clusters. Hence, in our example characterised by one singleton cluster (see Fig. 10), the resulting number of blood spatter patterns is two.

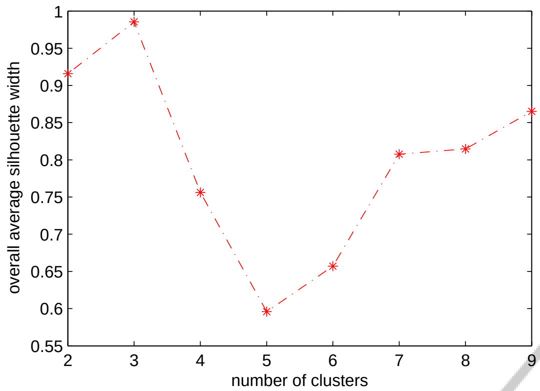


Figure 9: The overall average silhouette widths for each tested number of clusters *k*.

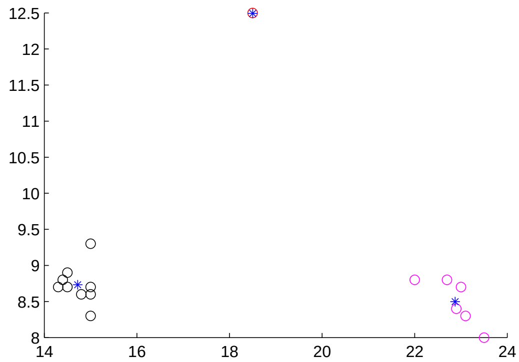


Figure 10: Output of Fuzzy C-Means for the number of clusters equals to 3.

Once identified the number of blood spatter patterns in a photograph, it is necessary to map the bloodstains to one of the identified patterns. This mapping is computed by considering the membership degrees of the pairwise points of convergence with respect to the computed clusters. In detail, the proposed approach assumes that a bloodstain belongs to the pattern/cluster for which the membership degrees of the pairwise points of convergence involving the bloodstain are higher. Precisely, for each bloodstain, a so-called *pattern membership value* is computed for each identified pattern/cluster by performing the mean of the membership degrees of pairwise points of convergence involving the bloodstain and belonging to the considered cluster. At the end, the bloodstain belongs to the cluster/pattern for which the computed pattern membership value is the highest. Once identified the blood spatter patterns and the relative bloodstains, the pairwise points of convergence involving bloodstains belonging to different patterns are removed from the set F since they are considered outliers. At this moment, the proposed system computes the center of the updated clusters (changed by removing outliers) which represents the point of convergence of the relative blood spatter pattern. By using the point of convergence and the angles of impact of each bloodstain belonging to the pattern, it possible to compute the point of origin of each pattern as described in section 2.

4 CONCLUSIONS

This position paper introduces a novel application domain in the area of computational intelligence: BPA. As proved by a preliminary study, fuzzy reasoning can strongly improve the capabilities of investigators in addressing BPA issues and try to solve complex cases in a faster and more precise way than current manual techniques. Our opinion is that BPA could represent a breakthrough application in computational intelligence community and open new research scenarios in a novel challenging area such as the Forensic Intelligence.

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