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# Robust estimation for area of origin in bloodstain pattern analysis via directional analysis

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ABSTRACT

Directional analysis provides quantitative data supporting the three-dimensional estimation of the area of origin for impact bloodstain pattern analysis. The final stage of directional analysis consists of calculating the point of origin via the arithmetic mean of top-view intersecting points and side-view heights of the virtual trajectories of single stains within the impact pattern. Given the sensitivity of the mean to the presence of outliers (droplets that have been influenced by gravitational force and aerodynamic drag), it is natural to ask whether directional analysis can be made more robust by modifying the averaging procedure. In this paper we focus our attention on two robust alternatives to the arithmetic mean: the trimmed mean and a deterministic version of the RANSAC algorithm. Our results suggest that the trimmed mean is a practical robust alternative to the arithmetic mean, whereas the deterministic RANSAC procedure is not. Since there can be no guarantee that stain selection can be free of outliers, the trimmed mean can be used as an aide in their detection. Moreover, our analysis reveals that the trimmed mean can also be used to detect outliers among the points of intersection of trajectories. Outliers of this type occur as the intersection points of trajectories emanating from stains with nearly vertical paths.



## 1. Introduction

The estimation of a blood source origin is one of the most essential pieces of evidence that can be extracted from a bloodletting crime scene. When a force is applied to a blood source, single bloodstains will fly through the air until striking a target surface. A bloodstain pattern area of origin is the three dimensional location of that blood source. Estimating the location by directional analysis consists of retracing the trajectories of a group of selected (upward directional) bloodstains that originated from this area. The trajectories are determined through trigonometric identities that relate the width and length of a stain (more precisely, of an ellipse that is carefully fitted to the stain) to the impact angle of the droplet and to the glancing angle of the bloodstain (the angle measured on the wall between the main axis of the stain and the vertical) [1]. Once the trajectories emanating from each stain have been retraced, obtaining the estimate of the origin is a simple procedure. The $x$ and $y$ coordinates of the estimate correspond to the arithmetic mean[1] of the $x$ and $y$ coordinates, respectively, of all the points on the $x$–$y$ plane (the top-view) where the retraced trajectories intersect (see Fig. 1).

When viewed from the side (on the $x$–$z$ plane), and fixing the $x$ coordinate of the origin, an upper limit for the $z$ coordinate is obtained as the mean of the $z$ values of the trajectories at that fixed level of $x$ (see Fig. 2).

The method of directional analysis as described above has been well documented and validated in the literature (see [1–5] and the references therein). Nevertheless, considering the sensitivity of the mean to the presence of outliers, it is natural to ask whether the method can be made more robust by modifying the averaging procedure. In this paper we focus our attention on two robust alternatives: the trimmed mean and a deterministic version of the RANSAC algorithm. We analyze and compare the performance of these statistics under two different settings. In the first setting (Case A), we consider impact patterns where all upward moving stains have been measured, and we take random samples of size 20 from all of the stains. In this situation the variance of the estimation is greatly reduced for all patterns when using the trimmed mean, with a small improvement in accuracy. Moreover, when stains were excluded from the samples according to the criteria for stain selection identified in [2], the reduction in variance was less pronounced in most cases, supporting the conclusion that those criteria can indeed help identify stains which affect the accuracy of the estimation negatively. We also study the more realistic setting (Case B) where only a small set of stains has been deliberately selected and measured by a bloodstain analyst

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[1] Henceforth we refer to the arithmetic mean simply as the mean.

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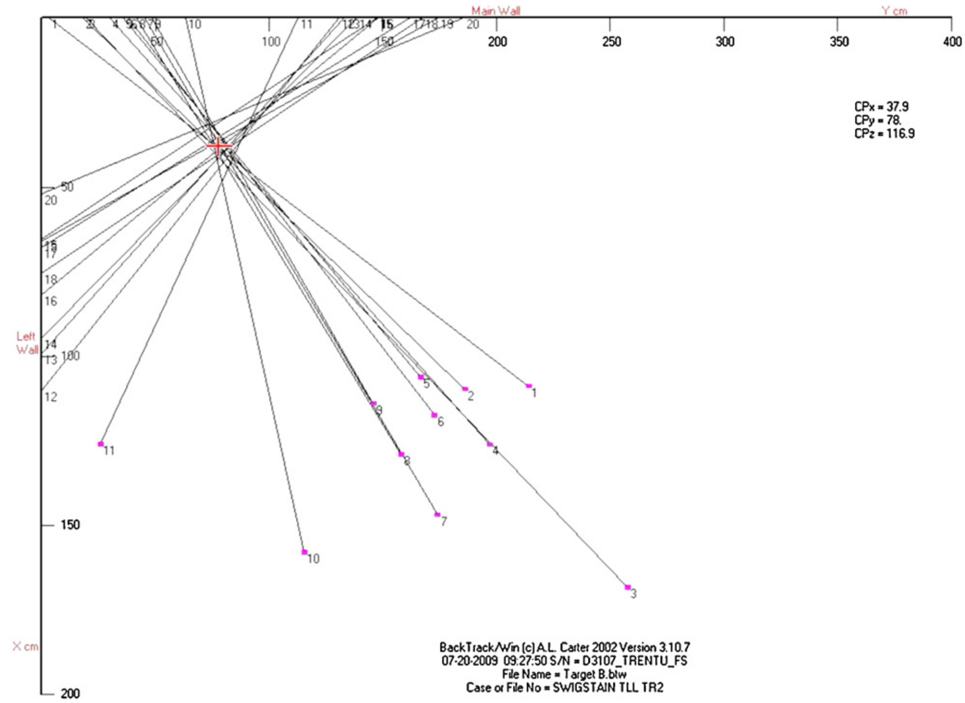



**Fig. 1.** Intersection of trajectories using Back Track$^{TM}$ top-view.

following standard selection procedures [2,3]. In this case we obtain no significant difference in the mean errors of estimation resulting from all three methods.

## 2. Methodology

### 2.1. Blood stain pattern data

The data used in this paper are from impact patterns created within a laboratory environment for past experiments, so that the true location of the source is known for each pattern. In Case A (patterns labeled as A1–A5 here), the data used were originally created and collected for analysis in [2]. Data for Case B (patterns labeled as B1–13 here) were originally created and collected for analysis in [4,5] and other similar research projects. The reader is referred to those papers for details in the methodology for pattern creation in each case. In each setting, information for all stains used here was initially collected and stored using BackTrack/Win$^{TM}$ and BackTrack/Images$^{TM}$. Using those packages, we obtained information on the retraced trajectories for all stains. After storing all the

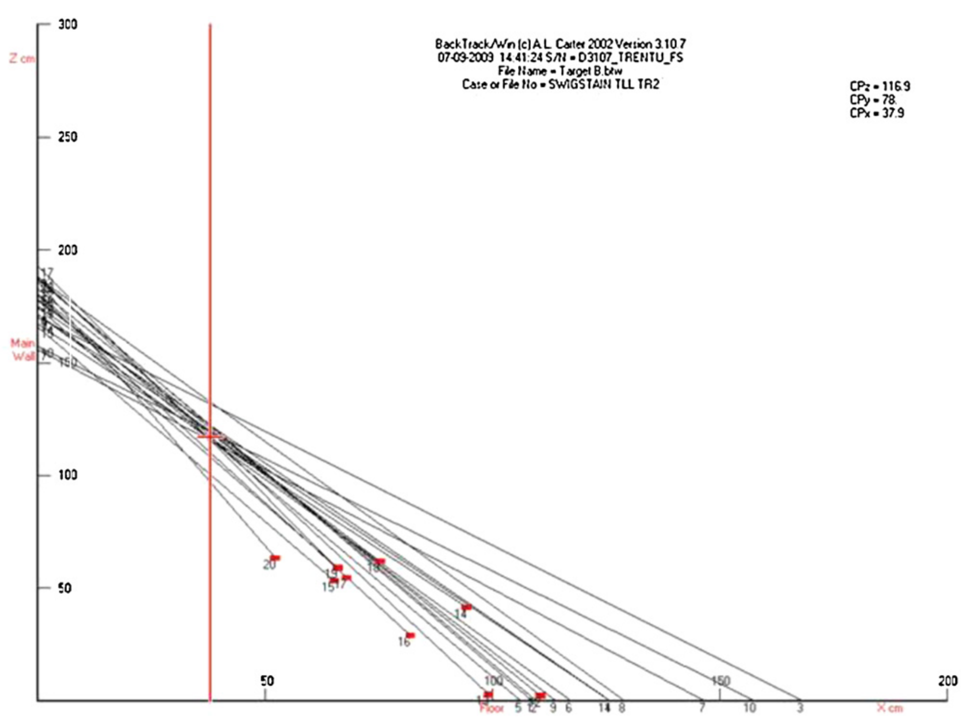



**Fig. 2.** Estimation of $z$ using Back Track$^{TM}$ side-view.

retraced trajectories in the appropriate format, we then performed all our calculations using the statistical language R [6].

### 2.2. Methods of estimation

The following three methods for computing the source of origin from the retraced trajectories will be compared. In what follows, we denote the estimated source of origin as $CP = (CPx, CPy, CPz)$. We recall that $CPz$ represents an upper bound for the true $z$ coordinate.

1. *Arithmetic mean*. This method corresponds to the basic top-view/side-view directional analysis procedure described in the introduction. Here the $x$ and $y$ components of all crossing points of trajectories on the $x$–$y$ plane are averaged (component by component) to obtain $CPx$ and $CPy$. Then $CPz$ is calculated as the mean on the $x$–$z$ plane (the side view) of the $z$ values on the projected trajectories at $x = CPx$.
2. *Trimmed mean*. We consider the same top-view/side-view directional analysis as in (1), but in both steps we use the trimmed mean for averaging the coordinates. A trimmed mean is computed by removing a percentage of the largest and smallest observations and averaging the values that remain. In contrast with the arithmetic mean, it is a measure of central tendency that is robust in the presence of outliers. The results presented here use a trimming percentage of 10%. We note that we also used the 20% trimmed mean, with very similar results to those discussed here.
3. *A deterministic version of RANSAC*. The RANSAC[2] algorithm is a method of parameter estimation in the presence of outliers developed and used for problems in computer vision. Its use for bloodstain pattern analysis was introduced in [7], where they use computer vision methods (namely, multiple-view geometry) as a different approach to source of origin estimation. Here we discuss the use of a RANSAC-like algorithm when estimating the source via directional analysis. Because in this context the number of stains used by the analyst is typically small, the usual random sampling and termination rule are not necessary, and the algorithm is greatly simplified, resulting in a deterministic version which performs a fixed number of operations. This can be done efficiently using R.[3] The algorithm we consider is the following:

i. Fix a value $d > 0$ (called the distance threshold).

ii. Repeat i) and ii) below for every pair of intersecting trajectories (two is the minimal number of trajectories required to make an estimate):
   i. Estimate the source of origin $CP$ from the top-view intersection of the two trajectories, together with the average of the $z$ coordinates of the pair of lines at the intersection.
   ii. Select the elements from the entire set of trajectories whose distance from the trajectory to $CP$ is less than $d$ (these elements form the consensus set CS for this pair, and are considered "inliers").

iii. The CS with the largest number of inliers is selected as optimal, and the source is recomputed using all the trajectories in the CS. In the presence of ties, the optimal CS is taken at random from all the tied CSs.

The distance threshold considered in this paper is $d = 2$ (chosen arbitrarily as a value that is neither too large nor too small). Values of $d = 1, 2.5$, and 3 were also considered, with very similar results. A modification where the distance threshold is allowed to vary is discussed below.

[2] RANSAC stands for RANdom Sample and Consensus algorithm.

[3] For a complete discussion of RANSAC, the reader is referred to [8].

### 2.3. Procedure

*Case A: random samples*. For each one of the five impact patterns A1–A5, a first set of 10,000 random samples of size 20 was selected from all available stains for that pattern, with 10 stains taken from each side of the pattern. The same sample was used to estimate the source via the three methods listed in Section 2.2. A second set of 10,000 random samples from each pattern was also selected. Stains qualifying as undesirable according to the outlier and zone criteria outlined in [2] were not included in this second set of samples. Once again, the source was estimated via the three methods using the same sample. The error of each estimate was calculated as the Euclidean distance between the known source of origin and the estimated source of origin. We note that henceforth we will refer to the second set of samples as the set with no outliers, with the clear understanding that some outliers are still present in the data set, except that these have not been identified a priori by us as obvious outliers or undesirable stains using the criteria stated in [2].

*Case B: samples selected by bloodstain analysts*. For each one of the thirteen selected sets of stains from patterns B1–B13, the source was estimated via the three methods listed in Section 2.2 and the error of the estimation was calculated.

## 3. Results and discussion

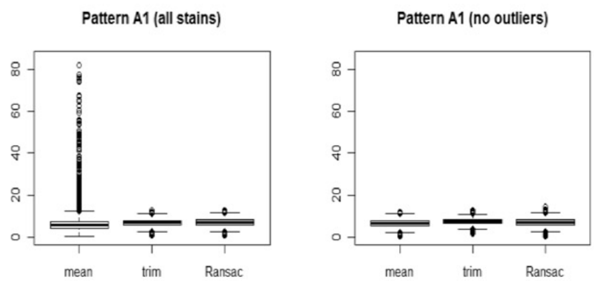
### 3.1. Case A: random samples.

Table 1 allows us to compare the variability in estimation for patterns A1–A5 for the three methods considered. The variable being plotted and summarized is the error of the estimates (the Euclidean distance between the known source of origin and the estimated one). A visual examination of the boxplots in the first column indicates that the trimmed mean is the measure that is most robust to the presence of outliers, producing estimates with the smallest variation and smallest maximum error for all patterns. The reduction in variability is less pronounced when stains identified as outliers are not included in the samples, which further supports the use of those criteria for the identification of undesirable stains. Although the Ransac procedure also reduces variability and maximum error in some cases, it does not perform well consistently, as can be seen in the boxplots for patterns A3–A5, and therefore we do not consider it further as a satisfactory robust alternative.

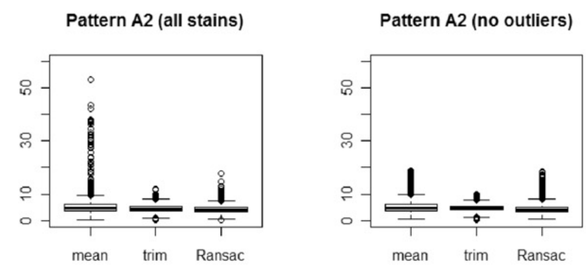
The maximum errors and variability are quantified in the second column of the table. The trimmed mean has the smallest standard deviation and the smallest maximum error for all patterns. The largest difference is observed for pattern A4 with all stains, where the standard deviation using the arithmetic mean is sixteen times larger than when using the trimmed mean (between 15.7 and 16.3 times larger, with 95% confidence), and the maximum error is reduced from 517 cm to 12 cm. The smallest improvement is for pattern A1 after outliers have been removed, and yet the standard deviation for the arithmetic mean is still significantly larger at 1.28 times that of the trimmed mean (between 1.25 and 1.30 times larger, with 95% confidence), although with no improvement on maximum error. We remark that although the error of estimation is known to increase as the true distance to the wall increases, we did not observe a relationship between the magnitude of improvement in standard deviation and the true distance to the wall.

When taking all patterns and samples into account, we found that the trimmed mean also improves the average error of estimation slightly. An average improvement of 2.8 cm is obtained when sampling from all stains ((2.6, 2.9) with 95% confidence), and an average improvement of 2.3 cm is obtained after removing obvious outliers ((2.1, 2.4) with 95% confidence). Although this

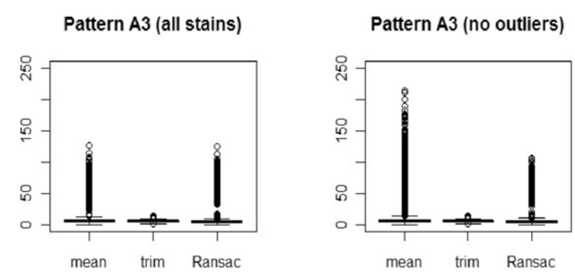
**Table 1**
Summary of variability and maximum error in estimation for Case A.



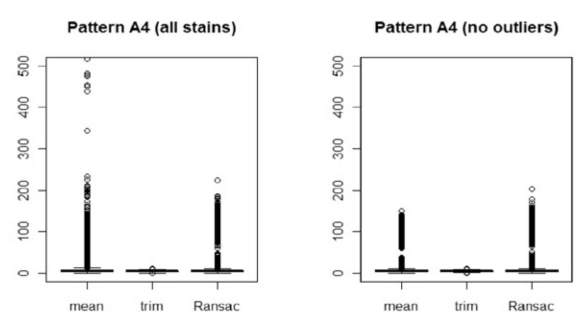

| Pattern | | Mean | Trim | Ransac |
|---|---|---|---|---|
| A1 (all stains) | Maximum error | 81.8 | 12.8 | 13.1 |
| | Standard deviation | 4.34 | 1.58 | 1.73 |
| A1 (no outliers) | Maximum error | 12.1 | 12.9 | 14.5 |
| | Standard deviation | 1.77 | 1.39 | 1.7 |



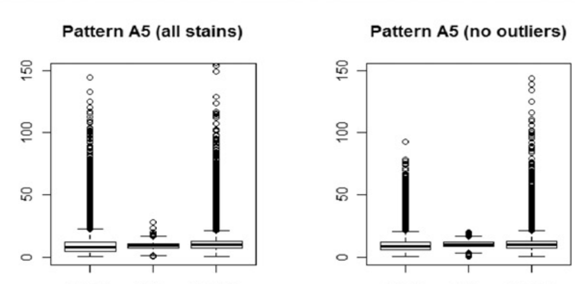

| Pattern | | Mean | Trim | Ransac |
|---|---|---|---|---|
| A2 (all stains) | Maximum error | 53.3 | 11.9 | 17.6 |
| | Standard deviation | 2.414 | 1.31 | 1.37 |
| A2 (no outliers) | Maximum error | 18.7 | 9.9 | 18.5 |
| | Standard deviation | 2.41 | 1.23 | 2.14 |




| Pattern | | Mean | trim | Ransac |
|---|---|---|---|---|
| A3 (all stains) | Maximum error | 126 | 13.9 | 125 |
| | Standard deviation | 15.17 | 1.58 | 16.01 |
| A3 (no outliers) | Maximum error | 276 | 14.4 | 106 |
| | Standard deviation | 20.22 | 1.54 | 15.09 |




| Pattern | | Mean | trim | Ransac |
|---|---|---|---|---|
| A4 (all stains) | Maximum error | 517 | 12 | 223 |
| | Standard deviation | 25.53 | 1.6 | 21.61 |
| A4 (no outliers) | Maximum Error | 151 | 10.7 | 204 |
| | Standard deviation | 20.48 | 1.52 | 22.5 |




| Pattern | | Mean | trim | Ransac |
|---|---|---|---|---|
| A5 (all stains) | Maximum error | 145 | 28.2 | 156 |
| | Standard deviation | 12.22 | 2.95 | 9.08 |
| A5 (no outliers) | Maximum error | 92.9 | 20.2 | 144 |
| | Standard deviation | 7.93 | 2.59 | 8.3 |

improvement does not seem important when averaging through all patterns and samples, its real importance comes to light when examining each pattern separately (pairing sample by sample), as we now discuss.

Table 2 summarizes the results when comparing the estimations using the arithmetic mean and those using the trimmed mean, paired sample by sample. The variable being summarized is the difference between the error of estimation using the mean minus the error of estimation using the trimmed mean based on the same set of stains. The fact that the median differences are either negative or very close to zero reveals that in about half the samples the trimmed mean actually increases the error of the estimation: when no real outliers are present, "good" stains are removed from the sample and this smaller sample results in a loss of accuracy. The largest loss is for pattern A5, with a difference of 12.5 cm. Being the pattern that is farthest from the wall ($x = 43.1$), estimation with fewer stains affects this pattern the most.

Nevertheless, even the biggest loss in accuracy is not very large, especially when compared to the large improvements observed in the presence of outliers. Careful examination of the sets of stains where these huge differences took place allows us to understand the reason behind those differences.

On the one hand, the presence of a single stain that is an extreme outlier can affect the estimation dramatically. Exactly how it is that an outlier affects the estimation can be seen in Fig. 3, where five stains taken from pattern A1, together with their retraced trajectories, are viewed on the $y$–$z$ plane. Stain 5 stands out as a clear outlier, resulting in a trajectory pointing in a completely different direction than the rest. A blood stain analyst adhering to accepted practices would discard such a stain from any estimation (it is in fact one of the stains discarded for the second set of samples from that pattern). The fact that discarding that stain is the right choice is made apparent by the sampling results of this pattern: every sample where the trimmed mean improved the estimation in more than 20 cm included this particular stain.

On the other hand, our analysis revealed that the trimmed mean can also improve the estimation dramatically when outliers occur, not among stains, but among points of intersection of trajectories. These outliers happen in patterns where at least two stains with nearly vertical paths (one on each side of the pattern) are present. When two stains have very similar gamma angles, both pointing straight down through the $y$–$z$ center, the intersection of their retraced trajectories is a point completely apart from all other intersections. When taking the mean, this point pulls the estimation away from the true source of origin.

As an extreme example we examine the worst sets of stains from pattern A5, all of which include the same two stains: stain 36 and stain 152. There are some reasons to consider stain 36 as a possible outlier, but we found no reason to regard stain 152 as one. Indeed, this is a situation where the problem is not caused by a single stain; the problem arises from the presence of both stains together. In particular, stains 36 and 152 have nearly vertical paths (with gamma angles of 354 and 358 degrees, respectively), so that the intersection of their retraced trajectories is a point completely away from all other intersections ($x = -4397$, $y = 124$, $z = 3482$). The resulting estimate for area of origin includes a value of $CPx = -33$, which would clearly be deemed absurd by any blood stain analyst, calling for further exploration of the data. However, for less extreme cases where the estimate is inaccurate but does not stand out as absurd, the phenomenon can be detected by the use of the trimmed mean.

### 3.2. Case B: samples selected by bloodstain analysts

We have seen that when considering random samples of stains, the trimmed mean performs better than both the arithmetic mean and the Ransac method when estimating source of origin via directional analysis. Be that as it may, we also need to analyze how the methods compare when the stains have been chosen with care by a bloodstain analyst, since that is how estimations are done in practice. Patterns B1–B13 are used for that purpose, and the results can be found in Table 3. With a single sample from each pattern, the only comparison that is possible here is the one between the average errors of estimation for each method. Note that the average error obtained with the Ransac method is larger than that of the mean, and that there is practically no difference between the average errors obtained for the mean and the trimmed mean. In fact, after adjusting for the effect of the true horizontal distance from the source to the wall (taking into account that the error of the estimation increases as the distance to the wall increases), we found no significant difference between the mean true errors for all three methods ($P > 0.2$).

We also evaluated the performance of another variation of the Ransac method – one that uses a criterion for finding the optimal consensus set (CS) that could not be applied earlier in the context of thousands of samples. This second criterion is often employed in cluster analysis when trying to find the natural number of clusters in a data set [9], and it involves looking for the number of clusters at which there is a knee, peak or dip in the plot of the evaluation measure against the number of clusters (here we use the sum of squared errors (SSE) as the evaluation measure). More precisely, instead of fixing a distance threshold arbitrarily, different values of the distance threshold are considered, and the size of the largest consensus set for each value is plotted against the SSE obtained from the estimation using that set. The optimal CS is then chosen as that one where there is a knee, peak or dip in the plot. When there is more than one CS to choose from, one can either pick the one with the lowest SSE, or obtain the estimate as the average of the estimates from all the candidate consensus sets.

**Table 2**
Summary for differences between error of estimation using the mean minus error of estimation using the trimmed mean for the same sample.

| | Pattern | Min. | Median | Mean | Max. | True $x$ |
|---|---|---|---|---|---|---|
| All Stains | A1 | −8.4 | −0.99 | −0.69 | 78.2 | 25.9 |
| | A2 | −6.3 | 0.26 | 0.36 | 47.3 | 17.8 |
| | A3 | −5.8 | 0.39 | 5.3 | 115.5 | 34.2 |
| | A4 | −6.0 | −0.14 | 6.76 | 515.6 | 27.7 |
| | A5 | −12.5 | −1.42 | 2.15 | 131.6 | 43.1 |
| No outliers | A1 | −6.8 | −0.60 | −0.83 | 6.22 | 25.9 |
| | A2 | −5.1 | 0.16 | 0.53 | 12.4 | 17.8 |
| | A3 | −5.7 | 0.03 | 6.89 | 272.1 | 34.2 |
| | A4 | −6.0 | −0.23 | 4.81 | 149 | 27.7 |
| | A5 | −10.7 | −1.23 | 0.037 | 81.6 | 43.1 |

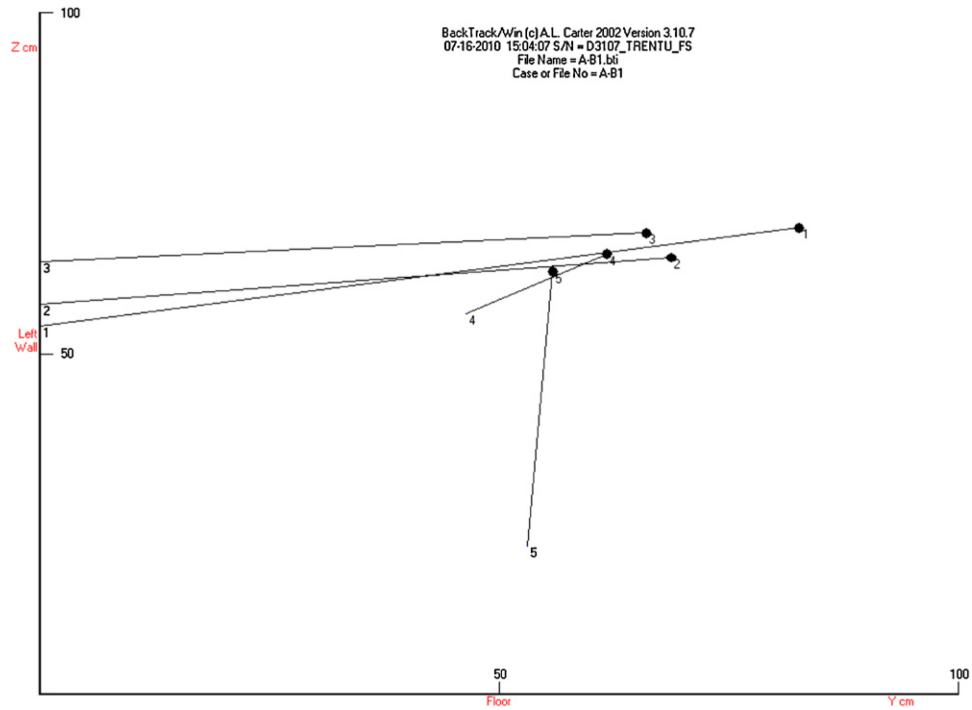



**Fig. 3.** Stain 5 stands out as a clear outlier among nearby stains.

**Table 3**
Comparison of errors for Case B.

| Pattern | Mean | Trim | Ransac |
|---|---|---|---|
| B1 | 13.23 | 14.1 | 15.22 |
| B2 | 10.46 | 10.03 | 7.68 |
| B3 | 11.77 | 12.65 | 9.55 |
| B4 | 2.66 | 2.57 | 3.49 |
| B5 | 10.95 | 10.75 | 17.45 |
| B6 | 8.87 | 9.19 | 7.22 |
| B7 | 5.07 | 5.12 | 4.53 |
| B8 | 15.31 | 14.38 | 19.2 |
| B9 | 3.84 | 3.38 | 3.29 |
| B10 | 8.45 | 8.43 | 11.06 |
| B11 | 5.01 | 5.47 | 8.0 |
| B12 | 22.44 | 23.13 | 28.87 |
| B13 | 3.82 | 2.56 | 0.38 |
| Average | 9.37 | 9.36 | 10.46 |

As an example, let us consider impact pattern B13 (a pattern with 20 stains). We obtained different estimations for the origin using a distance threshold varying from 10 cm (the CS is the complete set) to 1.6 cm (the CS has only 10 trajectories), calculating the SSE for each estimation. The plot of the cardinality of the consensus set against the SSE is found in Fig. 4. We observe a knee when the CS size is 17, so we pick that consensus set as the optimal one, and base our final estimation on it (clearly, the observation of a knee in the plot is highly subjective). With an error of only 0.6 cm, the estimation is in fact better than the original estimation (with error of 3.8 cm) and better than the trimmed mean estimation (with error of 2.6 cm). Unfortunately, the improvements using this technique were not consistent throughout the patterns. The lack of consistency, together with the extra computational burden of the method, disqualifies Ransac as a robust alternative to the standard directional analysis estimation using the mean. Although we do not see it as a practical alternative, Ransac has allowed us to confirm that a small number of well-selected stains can give a very accurate estimation of the source of origin.

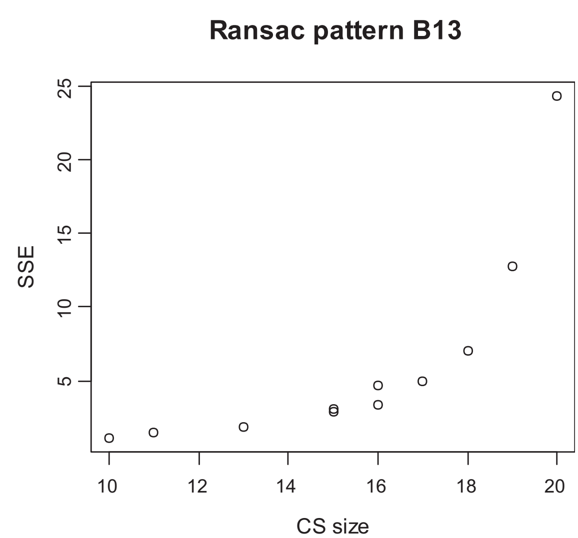



**Fig. 4.** SSE for consensus sets of different sizes.

## 4. Conclusions

From the calculations in Case A, we found that in the context of the source of origin estimation via directional analysis, the trimmed mean is a robust alternative to the arithmetic mean, whereas the Ransac method is not. Yet when applied to thirteen sets of stains that have been selected from a pattern by bloodstain analysts (Case B), the trimmed mean provided neither significant nor practical improvement in the estimation. This lack of improvement is a reflection of the absence of outliers in those sets of stains: when an analyst selects stains adhering to standard practices in the field (upward directional stains), extreme outliers are rare, so that among thirteen sets of stains we did not observe a single one. Since there is no guarantee that every selection can be free of outliers, particularly in more complex pattern analysis, such as the use of multiple surfaces, the trimmed mean can be used as an aide in the detection of outliers[4]. Indeed, a large difference between the estimation using the mean and that one using the trimmed mean can alert the analyst to the possible presence of an outlier (be it as a single stain or as an intersection point), calling for a closer examination of the data. If no strong reason for discarding a stain or an intersection point as outliers is found, then all stains and intersection points should be used and the estimation differences should be taken as an indication of the large variability in the data, so that caution must be exercised when interpreting results.

The results presented here are relevant to the forensic scientific community by way of validation of methods. Recent publications and court cases have challenged the robustness, validity, accuracy and reliability of many disciplines within the field of forensic science [10]. The statistical comparison of the methods for calculating a point for area of origin estimation supports the robustness of directional analysis and highlights the importance of stain selection in the process of estimation.

[4] Although the trimmed mean is not programmed directly in BackTrack™, it is easy to select the most extreme trajectory crossings manually from the top-view and discard them from the estimation.

## References

[1] A.L. Carter, The directional analysis of bloodstain patterns: theory and experimental validation, Can. Soc. Forensic Sci. J. 34 (2001) 173–189.
[2] M. Illes, M. Boué, Investigation of a model for stain selection in bloodstain pattern analysis, Can. Soc. Forensic Sci. J. 44 (2011) 1–12.
[3] J.K. Wells, Investigation of Factors Affecting the Region of Origin Estimate in Bloodstain Pattern Analysis, M.Sc. Thesis, University of Canterbury, Christchurch, 2006.
[4] A.L. Carter, Further validation of the BackTrack™ computer program for bloodstain pattern analysis – precision and accuracy, Int. Assoc. Bloodstain Pattern Analysts News 21 (2005) 15–22.
[5] A.L. Carter, J. Forsythe-Erman, V. Hawkes, M. Illes, P. Laturnus, G. Lefebvre, B. Yamashita, Validation of the BackTrack™ suite of programs for bloodstain pattern analysis, J. Forensic Iden. 56 (2006) 242–254.
[6] R Development Core Team, R: A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, Austria, 2011, ISBN 3-900051-07-0, http://www.R-project.org.
[7] J. Wright, A. Wagner, S. Rao, Y. Ma, Homography from coplanar ellipses with application to forensic blood splatter reconstruction, 2006, in: IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2006, 1250–1257.
[8] M. Fischler, R. Bolles, Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography, CACM 24 (1981) 381–395.
[9] P. Tan, M. Steinbach, V. Kumar, Data Mining, Pearson Education Inc., Boston, MA, 2006
[10] NAS, Strengthening Forensic Science in the United States: A Path Forward, National Academy of Sciences, Washington, 2009, S-16.