Innovative Forensic Features and Blood Spatter 3D Reconstruction from Geospatial-driven Datasets

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Received: 23 January 2025 | Revised: 28 March 2025 | Accepted: 7 April 2025

 DOI: https://doi.org/10.48084/etasr.10327

ABSTRACT

Crime scene documentation serves as the basis for reconstructing and interpreting evidence to provide forensic evaluation of crime events. The reliance on 2D photography for forensic features does not employ extensive documentation, as it limits the analytical properties of the captured data, such as 3D data fusion accurate scaling and innovative augmentation. This paper presents an innovative method to reconstruct forensic features and blood spatter using geospatial-driven datasets from multiple sources. The procedure involves a 3D reconstruction of a crime scene via geospatial techniques, namely Close-Range Photogrammetry (CRP) using an iPhone X smartphone camera and Terrestrial Laser Scanning (TLS) using a Faro Focus laser scanner. Meta Quest 2 was then used to transform the TLS point cloud into an immersive visualization. Meanwhile, an integrated point cloud model, transformed by the Iterative Closest Point (ICP) algorithm, was produced to examine the texture quality of the features being scanned, especially in blood spatter details. To determine the accuracy, the dimension measurements of the pieces of evidence were evaluated and analyzed using a two-sample t-test. The geometric property was extracted, showing that there were no significant differences between the mean-dimension measurements for all point samples. Additionally, the RGB values extracted from the point cloud datasets showed that CRP contributed to higher values compared to TLS. This shows that CRP facilitates more precise bloodstain pattern analysis compared to TLS.

Keywords-crime scene reconstruction; blood spatter; point cloud fusion; iterative closest point; terrestrial laser scanning; virtual reality

I. INTRODUCTION

A. *Crime Scene Documentation*

Crime scene documentation serves as the basis for reconstructing and interpreting the evidence to provide forensic evaluation of crime events. Traditional methods using photography, sketching, and manual measurements have been used for this purpose. However, these methods have some limitations, such as lack of precision, are time-consuming, and may not capture spatial relationships on the crime scene [1, 2].

The advancement of geospatial technologies, typically utilizing 3D point cloud data from various techniques such as Terrestrial Laser Scanning (TLS), photogrammetry, and LiDAR, has enabled crime scene recording with greater detail and improved accuracy. These approaches not only preserve information from the scene but also provide integrity, allowing specialists to revisit the crime scene more effectively [3]. Despite all these advantages, there are challenges in handling intricate details, such as small evidence, bloodstains, and other environmental factors that potentially affect data accuracy. The integration of geospatial technologies in forensic crime scene reconstruction has been explored through various studies, each addressing different challenges in capturing, analyzing, and interpreting crime scene data. Although advances in 3D reconstruction techniques such as LiDAR, photogrammetry, and laser scanning have enhanced forensic documentation, several limitations and gaps remain in handling intricate details and critical evidentiary material. This paper presents an innovative method to reconstruct forensic features and blood spatter using geospatial-driven datasets from multiple sources.

B. *Related Works*

In [4], the limitations of traditional crime scene documentation methods, such as measuring tapes and photography, were identified, showing that they are inefficient in capturing adequate details under time constraints. To address this, three 3D reconstruction methods were compared: iPhone LiDAR, Close-Range Photogrammetry (SfM CRP), and TLS. The results showed that iPhone LiDAR performed well in short-duration scans in daylight, while photogrammetry provided better accuracy for longer scanning periods. However, the research primarily focused on the overall crime scene rather than complex evidentiary details, such as blood spatter or small object reconstruction. In [5], the limitations of traditional 2D mug shots in forensic facial recognition were discussed, proposing a 3D facial reconstruction approach using photogrammetry. This study demonstrated that point clouds generated from photogrammetry effectively capture facial geometry with high accuracy. This advancement is significant for facial recognition; however, this could be potentially impactful if tested on complex forensic details such as bloodstains.

In [6], the limitations of relying on a single scanning system for forensic documentation were emphasized. This research proposed fusing TLS and CRP datasets to enhance 3D crime scene reconstruction, allowing for more precise spatial measurements. Although this approach improved the preservation of forensic materials, this study did not fully address critical evidence materials such as blood spatter, which poses challenges due to its inconsistent patterns and color variations. The fusion of datasets for more intricate evidence representation remained an area for further research. In a similar context, in [7], crime scene documentation using TLS and traditional photography was explored, recognizing that laser scanning alone was insufficient in capturing small evidence due to poor geometric representation. Although photography supplemented missing details, it was not an optimal solution for 3D reconstruction. In [8], it was shown how environmental lighting affects photogrammetry-based forensic archaeology reconstruction. By testing different lighting conditions, i.e. bright sunlight, harsh lighting, dappled lighting, and shadows, this study found that image quality and CRP model accuracy fluctuated based on illumination. Although this study focused on optimizing image-based documentation rather than full 3D reconstructions, texture-theme studies could be extended to crime scene evidence, especially for intricate and detailed forensic materials.

C. *Application of Geospatial Technologies in Crime Scene Documentation*

TLS and Structure from Motion (SfM) photogrammetry are two widely used geospatial technologies that provide dense detailing and highly realistic representations of crime scenes. They are commonly used in topographical and urban mapping, such as Building Information Modelling (BIM), Geographical Information Systems (GIS), urban planning, and many more. However, applying these techniques for non-topographic use, such as crime scene documentation, is not insignificant because 3D point data captures realistic and true-scale information about the scanned surface, including forensic subjects [9]. Tables I and II present examples of geospatial themes used in data manipulation and technology applications, respectively, for crime scene documentation works.

TABLE I. GEOSPATIAL THEMES USED IN DATA MANIPULATION FOR CRIME SCENE DOCUMENTATION

Theme	Insight
SfM [10]	Compared photogrammetric reconstruction methods using Agisoft Metashape and 3DF Zephyr on an archaeological site in Greece, evaluating performance, distance, and noise metrics, and discussing geo-visualization techniques for 3D model representation and manipulation
Texture-based [11]	Presented photogrammetry techniques for accurate 3D modeling of non-textured, transparent, or reflective surfaces in forensic documentation. 3D models were created with a focus on visual plausibility rather than quantitative metrics.
Automation [1]	Discussed the potential of geospatial virtual reality in forensic CSI and highlighted the advantages of laser scanning, photogrammetry, and VR to improve data management, time consumption, and user experience through 3D information and digital evidence preservation.
Virtual reality [12]	Used LiDAR scanning and Virtual Reality (VR) to enhance crime scene documentation and evaluated the effectiveness of point cloud-based reconstruction and VR walkthroughs.
Data fusion [13]	Suggested an integration of data derived from micro UAVs and TLS in forensic photogrammetry within a confined crime scene to provide a high-precision 3D model point cloud.

The nature of point clouds in geospatial fields not only offers a 3D point distribution on the subject, particularly an aligned coordinate system, but also improves the visualization aspect by preserving the original spatial relationship, including the colors and geometries of crime scenes [14]. Additionally, point cloud data are extendable into immersive presentations, such as VR, making crime scene revisiting more effective.

TABLE II. GEOSPATIAL THEMES USED IN TECHNOLOGY APPLICATIONS FOR CRIME SCENE DOCUMENTATION

Theme	Insight
3D Space [15]	Investigated the impact of filming techniques on 3D reconstructions using Neural Radiance Fields and Gaussian Splatting, identifying optimal methods for reducing noise and artifacts in indoor crime scene investigations and cultural heritage preservation.
LiDAR [4]	Besides highlighting the challenges faced by law enforcement in documenting scenes accurately and quickly under various conditions, this study also evaluated the effectiveness of mobile phone-based mapping technologies with LiDAR sensors for 3D crime scene reconstruction.
Aerial mapping [16]	Assessed the accuracy and dependability of reconstructed 3D modeling for vehicles at crash scenes using UAV and TLS data. The results demonstrated the high accuracy and efficiency of UAV technology in forensic mapping, which offers significant cost savings and enhanced safety.
3D scanning [17]	Evaluated the use of 3D pocket scanner software for the 3D recording of a small-scale crime scene and brought the breakthrough of creating 3D models of crime scenes in a fast, easy, and economical way using LiDAR technology.
CRP [8]	Applied CRP to record forensic archaeological scene recoveries in both open and wooded environments, finding that a tarp is a viable light correction tool to improve the visual quality of the final models by eliminating lighting inconsistencies.

D. *Translating Physical Features into the Geospatial Rigid Body Transformation Model for Digital Preservation*

3D reconstruction using geospatial techniques aims at accurately translating physical features into point cloud data using precise alignment techniques to ensure spatial consistency. This can be achieved by using a common registration method, known as the Iterative Closest Point (ICP). ICP is a mathematical method that integrates two corresponding points of different types of point cloud datasets. Usually, the datasets used are from different sources, e.g., TLS and photogrammetry. Each dataset used has different properties such as intensity, density, noise level, and point distribution. Therefore, to deal with these conditions, ICP was used to form a new point cloud model through a process known as the Rigid Body Transformation (RBT).

The algorithm calculates the distance between the two corresponding points, known as the Euclidean distance. This distance is then minimized until both points are matched. In other words, ICP works based on an estimation process where the positions of the corresponding points are minimized until they are optimally aligned [18]. This calculation is repeated until it meets its threshold, which indicates its iterative nature in point alignment based on a rotation matrix R and the translation vector T. The equation of point alignment under the RBT process is as follows:

$$f(R,T) = \frac{1}{k} - \sum_{i=1}^{k} \left\| q_i - \left(R_{p_i} + T\right) \right\|^2 \quad (1)$$

where $f(R,T)$ is the estimated transformation, R is the rotation matrix, T is the translation vector, pi are the 3D coordinates of point cloud P, and q_i are the 3D coordinates of the point cloud Q. Point matching is carried out by iteratively aligning the positions of both correspondent points. For example, the coordinate of dataset P indicated as p_i is aligned with the coordinate of dataset Q indicated as q_i. Assuming the coordinates of the 3D points from the P and Q datasets:

$$P = \{p_i \mid 1 = 1, 2, 3 \ldots\} \quad (1)$$

$$Q = \{q_i \mid 1 = 1, 2, 3 \ldots\} \quad (2)$$

This mathematical approach enables seamless fusion of spatial data and enhances the accuracy of 3D models for forensic reconstructions, geospatial applications, and other fields that require precise multi-source data integration.

II. METHODOLOGY

A. *Procedural Configuration*

The procedure involves 3D reconstruction using geospatial techniques, namely CRP and TLS. CRP via an iPhone X smartphone covered the blood spatter region due to its advantage of providing a textured point cloud with intricate details. Meanwhile, a Faro Focus TLS was critically important for capturing the overall scene with millions of colored points for accurate spatial measurements involving points, polygons, and lines of data. In this data collection, the sphere target marker was used for point cloud registration. ICP was used to create highly detailed point data for evidence documentation, such as blood spatter analysis. After integrating both datasets (CRP and TLS) using the ICP method, the TLS dataset was transformed into a VR environment to extend the visualization of blood spatter in an immersive environment. Figure 2 presents the procedural design of this work.

For simulation of the crime scene and evidentiary details, Figure 1 shows a mannequin covered with fake blood and placed next to the knife to give the impression that an incident had occurred. Furthermore, the objects were placed as pieces of evidence. The scene was also marked with evidence identification markers, as typically done by investigators at the crime scene. For checking purposes, the generated point cloud from both methods, TLS and CRP, was referenced to the measurement taken with Vernier Calipers (VC) to achieve millimeter-level accuracy.

Fig. 1. Setting up a mock crime scene.

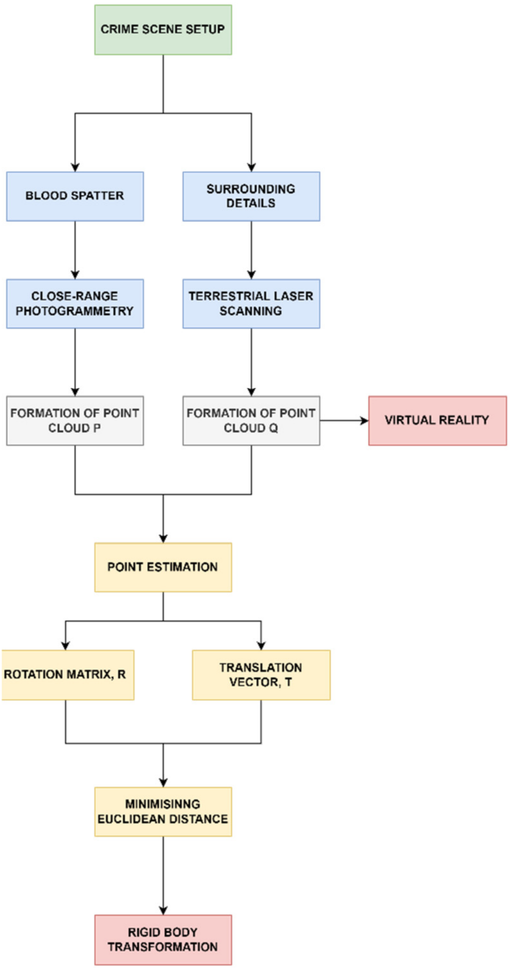

Fig. 2. Procedural design of this work.

Fig. 3. 3D scanning using Faro Focus laser scanner.

B. Data Processing

The TLS data were imported in the form of a raw point cloud. Scanning was preregistered and aligned with the help of VIS technology during the on-site scanning process. VIS technology, which stands for Visual Inertial System technology, uses a combination of visual and inertial sensors to track the position and motion of devices in three dimensions. Laser scanning uses this technology for the process of registering scans from different positions and to enable real-time coordination between scanners, reducing the need for post-processing. The data were then exported and encoded in .las format. The scale of the point cloud was set to 1:1, which is the standard for designing VR experiences. The 1:1 scale means that the scale in the virtual world is supposed to be the same as in the real world. The 3D point cloud was visualized using VR technology through VR Sketch through SketchUp software and the Head-Mounted Display (HMD) Meta Quest 2, as shown in Figure 4. Using a two-handed controller, users can orbit, zoom, and pan around the 3D space, changing their viewpoints as they interact with the visual environment. The VR Sketch application offers a distinctive teleportation ability that enables users to relocate their viewpoint to a designated teleportation point, while also providing a 1:1 visualization of the associated 3D model [19].

Fig. 4. Importing point cloud into Meta Quest 2 virtual reality.

Then the TLS-CRP datasets were integrated. First, the raw data (in. fls or .fws file format) from the TLS were imported into Faro Scene software and went through manual registration for the set of scans by selecting the sphere (target marker) as matching points, resulting in a merged point cloud. This was followed by noise filtering (known as data cleanup) and colorization, to obtain a smooth point cloud output. Second, the images captured by the smartphone were configured for SfM photogrammetric processing. There were several phases involved, namely image alignment, point cloud generation, dense point cloud generation, and meshing. The SfM technique offers fast and robust point cloud generation driven by photographic texture influence [20].

Moving forward, the TLS-CRP datasets were processed using CloudCompare, an open-source 3D point cloud processing software widely used for geospatial and computer vision applications. Within CloudCompare, both datasets were aligned using the Iterative Closest Point (ICP) algorithm, a method that iteratively minimizes spatial discrepancies between the corresponding points. This alignment process ensured that the TLS and CRP datasets shared the same coordinate system, allowing for seamless data integration and improving spatial accuracy [21]. Therefore, by aligning the datasets, discrepancies caused by variations in scale, orientation, or positioning were reduced.

Fig. 5. Point alignment between point-based point cloud (TLS) and texture-based point cloud (CRP).

III. RESULTS AND ANALYSIS

A. Analysis of Geometric Properties

Four scan files were collected for this research. According to the data obtained from the scans, 42,212,156 dense point clouds were produced, of which 41,487,167 points were exported for further measurement extraction and visualization. The point cloud data were successfully gathered and rendered in VR. In terms of qualitative analysis, the output of the point cloud data contains visible voids and noise, such as the knife, phone, and purse (Figure 6). The texture of the 3D point cloud appears to be poor due to the presence of noise.

Fig. 6. Voids and noise are present in the point cloud.

Fig. 7. Integrated feature points of blood spatter and surrounding details of a crime scene.

For the TLS dataset, the dimension measurements of the evidence were extracted from VC, and the measured points were extracted from both the geospatial-derived point cloud and the VR Sketch model, upon which a two-sample t-test was performed. The two-sample t-test is a common way to determine whether there are significant differences in means and variances between a control and a recovered group [22]. Conventional two-sample t-tests examine whether the distributions' means are equal. The standard deviations of the samples are assumed to be the same and represent a common standard deviation in this test. The hypotheses for the two-sample t-test were as follows:

- H0 (null): μ1 = μ2 (Mean dimension measurements of the pieces of evidence are the same),
- H1 (alternative): μ1 ≠ μ2 (Mean dimension measurements of the pieces of evidence are not the same).

The statistical test is calculated based on:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{s_p\sqrt{\frac{1}{n_1}+\frac{1}{n_2}}} \quad (4)$$

where $\bar{x}_1$ and $\bar{x}_2$ are the means of sample sizes, n_1 and n_2 are sample sizes, and s_p is the pooled standard deviation.

For the TLS-CRP data, the measurements were extracted from tape, TLS, and CRP. The Root Mean Squared Error (RMSE) of the data was calculated based on (5). RMSE is frequently used to measure the accuracy of predictive scoring systems, and a lower RMSE value indicates higher accuracy. It is more specifically defined as the sum of the squares of the difference between the observed and the true values [23].

$$RMSE = \sqrt{\frac{\Sigma\,(x_e - x_O)^2}{N}} \quad (5)$$

where x_e is the true value, the measurement from the tape, x_O is the observed value, the measurement from TLS and CRP, and N is the total number of observations.

To determine accuracy, the dimension measurements of the pieces of evidence were evaluated and analyzed using a two-sample t-test. Table III displays the sample statistics of sample measurements extracted from the point cloud data that represent the evidence from the crime scene simulation.

TABLE III. SAMPLE STATISTICS

Sample statistics	Measurement extraction method		
	VC	**TLS**	**VR**
Mean	87.265	85.552	85.100
Standard deviation	30.901	33.617	34.236
Standard error mean	9.772	10.631	10.826

In statistical hypothesis testing, such as the two-sample t-test, the critical value of t determines whether a difference between two sample means is statistically significant or random. As shown in Table IV, the critical value of t between the three samples is 2.101, while the t value for each sample is less than the critical value of t, which does not reject the null hypothesis. At the significance level $\alpha = 0.05$, the p-value for the three samples is greater than the chosen significance level. Therefore, the null hypothesis is not rejected, which means that there is no significant difference between the mean dimension measurements of the pieces of evidence extracted from the three different methods. According to Table IV, the standard error value for VC-TLS is lower than the value for VC-VR because the TLS data retain their original data, whereas the data viewed in VR have undergone a conversion or filtering process that can produce spatial data loss.

TABLE IV. SAMPLE STATISTICS

Sample statistics	Measurement extraction method		
	VC-TLS	**VC–VR**	**TLS-VR**
Mean	1.713	2.165	0.452
Standard error	14.439	14.584	15.173
t Critical (two-tailed)	2.101	2.101	2.101
t	0.119	0.148	0.030
df	18	18	18
p-value (two-tailed)	0.907	0.884	0.977

Based on the analysis of the point cloud, it was determined that a medium scan density is sufficient to enable the generation of high-quality 3D data at the required resolution. Furthermore, the 3D simulation of the crime scene displayed adequate spatial detail, although some noise was present in the simulation. The voids and noise observed in the point cloud data appear to be the result of a combination of factors, such as reflective and dark objects at the simulated crime scene and the laser scanner that was used to acquire the data. In [24], transparent and highly reflective surfaces, such as shiny or mirror-shaped surfaces (evidence marker, door glass, and mannequin in this research), as well as black or generally dark materials, were found to cause voids in the 3D point cloud. As a result of these materials and their properties, it is exceedingly difficult for optical imaging instruments to capture them, which means that they are often a major obstacle for optical 3D imaging. In [13], the RMSE values for certain elements were higher, which was attributed to noise present in the 3D point cloud model or to the reflective characteristics of the elements.

In terms of measuring the dimensions of the evidence, measuring in the geospatial model seemed to be much simpler and more accurate compared to VR Sketch due to the ability to select two precise points of the point cloud. For measuring points in VR Sketch, there were no specific points to select from; thus, certain positions in the 3D space were selected for the measurement. It is important to perform an approximate point selection in VR Sketch to identify the identical points that were selected in the geospatial model. This means that in a point cloud environment, it was possible to interact with the points; however, it was not possible in VR Sketch.

Another aspect to consider when measuring VR Sketch is the Z axis, as it may have an impact on the accuracy evaluation. Since there are no precise points to select, the user is required to adjust the orientation of the 3D point cloud to approximate the X, Y, and Z coordinates of the corresponding points that were selected in the geospatial model. The findings indicate that VR enhances the experience of being on a crime scene and enables the user to examine the spatial relationships between the evidence.

B. RGB Extraction Analysis

The results show that CRP consistently yielded higher RGB values compared to TLS, which can enhance the visualization of critical evidence, such as bloodstains, while also capturing the surrounding features of the scene. This allows for a more comprehensive understanding of the spatial relationships and context of the evidence. Figure 8 shows the distribution of RGB points within the reconstructed crime scene, and the extracted values are presented in Tables V and VI. Based on Tables V and VI, the higher RGB values obtained through the CRP method are primarily attributed to the use of high-resolution cameras and controlled lighting conditions during image capture, resulting in vibrant colors and enhanced detail. In addition, the influence of textures on photographic details could be useful for evidence recognition. Therefore, the interpretation of critical forensic details such as blood spatters is effective. Additionally, the ability to accurately represent these details is important in forensic analysis, as it helps investigators understand the dynamics of the crime scene, including positioning. By providing a clearer visual representation of bloodstains, CRP facilitates more precise bloodstain pattern analysis compared to TLS.

Fig. 8. Distribution of RGB points within the reconstructed crime scene.

TABLE V. RGB VALUES FOR CRP POINT CLOUD

Sample ID	CRP			Color code
	R	G	B	
1	158	57	51	
2	157	112	128	
3	202	118	117	
4	190	130	111	
5	146	76	71	
6	171	113	114	

TABLE VI. RGB VALUES FOR TLS POINT CLOUD

Sample ID	TLS			Color code
	R	G	B	
1	109	24	22	
2	133	38	32	
3	162	64	58	
4	196	115	95	
5	176	92	77	
6	197	112	91	

On the contrary, although TLS is known for its high precision in capturing the overall geometry of a scene, the RGB values it produces can be lower and are often influenced by environmental factors and scanner settings. TLS excels in documenting the surrounding features of the crime scene, such as walls, furniture, and other structural elements, but may not capture the fine details of evidence such as bloodstains as effectively as CRP. This limitation underscores the importance of integrating both methods into crime scene reconstruction. By combining high-detail RGB data from CRP with the comprehensive spatial coverage provided by TLS, investigators can create a more holistic and accurate representation of the crime scene.

IV. CONCLUSION

Using the TLS technique, 3D information was processed within a point-cloud engine and visually presented in VR Sketch using SketchUp software. The findings of this study indicate that there is no statistical significance between the samples; therefore, the level of accuracy is deemed suitable for data visualization purposes. In conclusion, the use of TLS instruments can significantly accelerate the process of obtaining data from the crime scene. Using together a 3D point cloud and VR could make it easier for the investigator to understand and analyze the evidence of the crime scene that is to be presented to the court more efficiently. This research utilized TLS for data collection since it can produce large point cloud datasets at a very high speed; however, the surface of the objects being scanned must be taken into account to ensure accuracy. The level of accuracy in scanning depends on the material properties of the item being scanned and the accuracy at which the measurement points are chosen. The combination of TLS and CRP data enhances 3D representations of crime scenes, particularly for blood stain analysis, which involves small details. A detailed 3D model is essential for an accurate assessment. The integration of both data types improves texture, color, and visual quality, which makes it advisable to combine them. Relying solely on TLS point clouds may not provide sufficient color and texture intensity for thorough analyses, such as bloodstain evaluation.

ACKNOWLEDGMENT

The authors highly acknowledge Universiti Teknologi Malaysia (UTM) for financial support under Potential Academic Staff (PAS) Q.J130000.2752.03K82. Special thanks to Photo Laser Grammetry Sdn. Bhd. UTM Spin-Off Company (940142-X) for their sponsors and research facilities.

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