A dataset to test AI on forensic scenes

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Abstract

The aim of this article is to describe a dataset derived from crime scenes or fictitious accidents that can be used for artificial intelligence processing. The steps involved in setting up these forensic scenes, the data acquisition chain, classification and formatting will be described, as well as the first tests carried out in artificial intelligence. The first data formatting operations will be carried out so that they can be integrated into machine learning and deep learning solutions; in particular the deep learning solution SuperPointTransformer (Robert et al., 2023). The difficulties linked to this type of work and the benefits of using artificial intelligence for forensic scenes will also be presented.

1. Introduction

With the development of photogrammetry (2000s) and the advent of laser scanners (2005-2010), the field of forensic science began to take an interest in scene digitization techniques for both indoor and outdoor crime scenes, as well as accidents (road, air, rail, *etc.*). The term "digital crime scene or accident scene twin" began to appear in 2015 within the technical and forensic police services. It was not until 2024, during the "Petit Émile" case (France3-EmileSoleil, 2024), that the term was used publicly in a French legal proceeding. When we take a closer look at these digital twins, we realize that, in the field of forensic science, they are often reduced to three-dimensional modelling and that they have evolved relatively little since their inception.

However, when we look at recent definitions of digital twins, we realize that in other fields, such as construction or industry, the term digital twin is more complex and is not limited to a 3D model (Grieves and Vickers, 2017; Glaessgen and Stargel, 2012). Beyond the aspect of a 'twin' of a physical element, the digital twin must also be considered in terms of information exchange. Indeed, according to (Tao et al., 2018), "Digital Twin consists of three parts: physical product, virtual product, and connected data that tie the physical and virtual product". It is therefore interesting to be able to take an interest in the information that can complement these digital twins, a real vector for increasing their potential.

2. Information and digital twin in forensic science

2.1 Information available

Regarding information exchange, we immediately think about all the external data that could be integrated. External data can be very different in nature. It can be linked to the traces present in the scene, to images that may have been acquired during the observation phases but also before, as well as data from IOTs (Bouchaud et al., 2018) or electronic devices present in the scene or nearby, *etc.* When we think about this a little further, we realize that one obvious source of data is poorly exploited: the 3D model and one of its constituent elements: the point cloud. In forensic science, the point cloud is used in blood trace morpho-analysis calculations (Buck et al. 2011), ballistic trajectories or in accidentology (Guan et al., 2013; Baier et al., 2020). The cloud is vastly underused in terms of all the possible forensic applications.

2.2 Intrinsic information

It's interesting to ask what intrinsic elements of the point cloud might be of interest in forensic science. First of all, if we restrict ourselves to the areas mentioned above, the area of blood traces raises a question. Most of the calculations made using a 3D point cloud are based on the assumption that the object must be flat, onto which a photograph of the bloodstains will be projected. In fact, thanks to this application of a photograph on a plane, it will be possible to determine the ellipses resulting from the blood projection and thus, by calculating an inverse trajectory, to trace the blood's point of origin (FaroZone, 2024).

However, it has never been verified that the object onto which the photograph is projected is flat. The detection of flat elements is therefore a fundamental element in the context of a scene with reddish marks. The search for an ellipse and the calculation of the inverse trajectory to lead to the position of blood origin would then be distorted. In particular, plastering photographs of traces of blood on a slightly curved wall would inevitably lead to an error in the position of origin of the blood, which corresponds to the position of the injury on the victim. It is essential to take these factors into account, as miscalculating the position of the victim can lead to the facts being classified in a different way. For example, if the victim was standing, this may be consistent with a struggle with the perpetrator, whereas if he was kneeling, this may suggest that the victim was submissive. This could lead to the crime being classified as manslaughter, deliberate homicide or even murder.

The search for other objects such as furniture, bodies, external elements added to the scene (e.g. markers: triangular markers with black numerary or letter indications) would certainly provide essential information to technicians, experts or investigators. In particular, the markers could prove fundamental in the context of automating the integration of information. To be able to link elements together, it is necessary to have a unique primary key for the entire scene. The index number could be used for this purpose. If the additional information also included this primary key, the potential for automatic integration of additional information would appear, as is the case in a geographic information system (de Leeuwe, 2017). This new possibility would save a considerable amount of time, if only for determining the nature of the objects collected.

In the case of an air crash, a great number of items must be removed, both because of the large number of victims and because of the number of aircraft parts. For example, an Airbus A380 may have 615 seats on board (Emirates, 2024). In the event of a high kinetic impact, there is a high probability that the bodies and the aircraft will break up, which means that a very large number of components will have to be analyzed. This highlights the importance of automating these operations.

2.3 Detection of intrinsic information

In the previous paragraph, we saw the value of detecting elements intrinsic to the point cloud. It is now important to see how they can be detected. The software solutions used in forensics include manual or automatic feature detection tools (e.g. plane, sphere and ballistic trajectory detection (Liscio et al., 2020)). However, for more complex objects, segmentation tools are not available in forensic science. The manual approach will not be developed further here, as it is of no particular interest, particularly in terms of time cost. Instead, we will focus on automatic approaches, in particular using emerging artificial intelligence technologies.

Initially, we looked at machine learning to see what simple operations these processes could help with. To go a step further, and after reading the segmentation tools available in the literature, a deep learning solution proved interesting to test, in particular because of the results presented but also because of the relative ease of implementation. This solution, developed by (Robert et al., 2023), is called the "SuperPoint Transformer". Before we could look at these processes, we needed suitable data.

3. Data acquisition methodology

3.1 Fictional crime scenes

To test data processing tools, it is necessary to have digital twins of forensic scenes.

For obvious reasons of confidentiality, the aim being to be able to make the results of our work available to the scientific community, real scenes could not be used. To overcome this problem, it was decided to set up fictitious crime or accident scenes. During the last academic year, 57 fictitious scenes were set up at the Lausanne Criminal School of Justice.

These crime scenes, sometimes set up just for the occasion or borrowed from practical work as part of student courses, are intended to be as realistic as possible. They take on the characteristics of real scenes. A representative range of real crime scenes can be found, such as homicide, rape, kidnapping, discovery of a corpse, *etc.*

Figure 1: Fictional crime scene th_002: kidnapping - homocide, index markers on yellow

The markers are represented by triangular plastic objects, yellow in color and numbered in black.

To make detection operations using artificial intelligence more complex, the markers are not always numbered in ascending order and some numbers are omitted, as can also be the case in real scenes (broken, dirty marker, missing from a set, *etc.*). These markers are always placed in the immediate vicinity of the object(s) they designate. A single jumper can be used to designate a single object or a set of identical or similar objects (*e.g.* several cans placed next to each other). As mentioned above, index markers have been placed on the traces of interest, but some scenes do not have index markers in order to check the presence or absence of false positives in the treatment solutions.

Figure 2 : Close-up of tracks with triangular markers with black numerary indications nos. 18, 21, 60

When we work in the field of forensic science, we don't primarily talk about clues or evidence. The first thing we talk about is traces. According to the principle of (Locard, 1920), traces are produced during criminal action: "No one can act with the intensity that criminal action presupposes without leaving multiple marks of his passage". Indeed, to take a simple example, if two people meet and one of them touches the other's arm, the first may leave its DNA on the sleeve of the second person; just as fibers from the coat of the second person may be found on the hand of the first.

These traces can be very different in nature: reddish traces (we're not talking about blood here until we can verify this), gunpowder traces linked to a firearm shot, shoe tread traces, and so on. Once a trace has been produced, it will be necessary to fix the scene of the crime or accident as rigorously as possible. In fact, Bischoff (1938) has already shown this importance by stating that "the findings are the cornerstone of any trial" (translated from French). If the findings are poorly made or incomplete, it is impossible to go back and recover elements that disappear over time. We can see how important it is to keep looking for innovative solutions to help us better understand the scene and the related processing operations.

To ensure compatibility with machine learning or deep learning solutions, which are two sub-sections of Artificial Intelligence (Pellis, 2023), we have chosen to limit these crime or accident

scenes to small ones. These scenes have a maximum size of 10 by 10 meters. Larger scenes would require more 3D acquisitions or documentation, which would mean a very large volume of data that would then have to be processed. However, according to (Robert SuperPoint Transformer, 2024), we can already see the limitations of certain deep learning solutions that recommend a reduced number of points for the analysis of point clouds. These scenes can be either indoor or outdoor, as may be the case in real life.
To better understand the results of the crime scenes and accident scenes, all of these scenes were listed in a spreadsheet called "Spreadsheet_General_Description.xls" and named "Th_0001" to "Th_0057". The date and place of installation, the type of scene, the number of index markers and the main elements to be sampled are also indicated in this spreadsheet.

Date	Name	Location	Type
27.02.2024	Th_0002	Interior, Batochime, ground floor	Kidnapping
27.02.2024	Th_0003	Interior, Batochime, ground floor	Homicide
27.02.2024	Th_0004	Interior, Batochime, ground floor	Surdose / drug trafficking
27.02.2024	Th_0005	Interior, Batochime, 7th floor	Kidnapping / drug trafficking
27.02.2024	Th_0006	Interior, Batochime, 7th floor	Homicide

Table 1: First columns of the general scene description table “tableur_descriptif_general.xls”

Number of markers	Markers number	Main traces
14	11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 32, 35, 60	body, link, serreflex, baillon, …
8	11, 12, 16, 17, 18, 20, 21, 32	Wallet, glasses, knife, syringe, …
8	11, 12, 16, 17, 18, 20, 21, 32	Body, briefcase, glove, cash
9	1, 14, 19, 22, 23, 35, 69, 72, 90	drug, safe-deposit box, letter
11	11, 12, 13, 15, 16, 17, 18, 20, 21, 32, 60	body, 12-gauge holster, 9mm holster, shotgun, crowbar

Table 2: Information about the markers and related indexes that can be found in the general scene description table “tableur_descriptif_general.xls”

3.2 Digitization and documentation

When the question of digitizing scenes arose, several options were possible, in particular two techniques: photogrammetry and laserscanning.

Initially, we focused on photogrammetry. After several tests, we realized that many photographs were needed to digitize scenes measuring 10 meters by 10 meters. What's more, a difficulty very quickly became apparent: that of being able to take overlapping photographs while always trying to respect the same ratio, which makes taking photos more complex. What's more, some of the scenes are very homogeneous, particularly the walls and ceilings. This implies a computer processing difficulty in calculating a point cloud, even if new developments are being made to solve certain difficulties as set out (Haruki et al., 2024). What's more, having many photographs to process requires appropriate machine processing capabilities. Furthermore, since the aim is to be able to process the data in AI, with photogrammetry we do not control the number of points in the cloud obtained after photogrammetric processing. For all these reasons, photogrammetry was not used in our case study.

We then turned our attention to terrestrial laserscanning. We had at our disposal a Premium model Faro Terrestrial Laser Scanner, like that used in many forensic units dealing with crime or accident scenes. After obtaining information from various forensic science departments, we realized that we needed to be able to scan with sufficient accuracy while guaranteeing a short acquisition time. Indeed, the aim of crime scene technicians or experts is to be able to take a scene into account quickly before the traces gradually disappear. In the case of an outdoor scene, rain and wind can, for example, cause elements to disappear or move around. Furthermore, in cases involving ballistics or morpho-analysis of traces, a certain degree of precision is required to be able to calculate ballistic trajectories or the reverse trajectory of blood droplets.

With the laser scanner at our disposal, we tested various acquisition parameters to examine the acquisition time, number of points and measurement accuracy. Generally speaking, it is not always necessary to scan in color for a forensic scene, but in this case, in order to have a wider range of data to process, we were interested in parameters that also included colour scanning (which de facto takes longer to acquire than in black and white). Following this study, and in order to meet the requirements in terms of scanning time and accuracy, the following parameters were selected:

Parameter	Time of digitization	Number of points	Accuracy
Resolution ¼, quality 2	3min27s	42.8 Mio	6mm/ 10m

Table 3: scanning parameters selected for Faro Premium laser scanner

After several tests on indoor and outdoor building elements, the 3D point clouds obtained using these parameters were found to be of interest for establishing the state of a forensic scene. Laserscanning was therefore chosen as the technique for digitizing forensic scenes. To obtain usable information, the 3D data from the acquisition will then be processed using Faro Scene software, in particular for the colourisation and export phases. The choice was made to export the data in “.las” format, which is compatible with a number of processing solutions. The various steps in the 3D digitization process are shown in the diagram below:

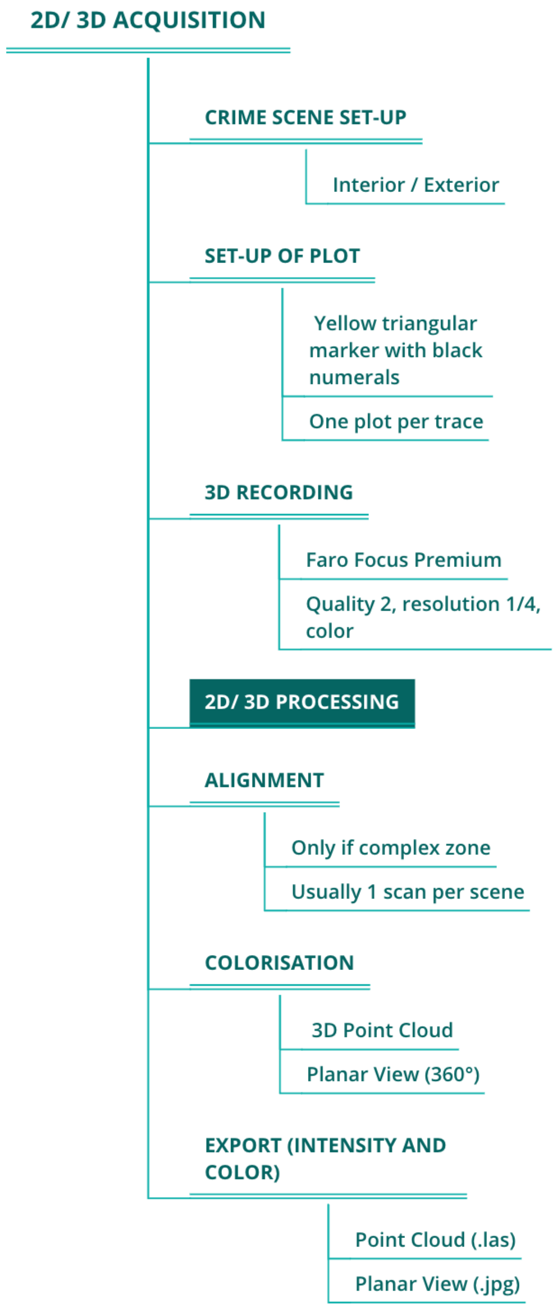

Figure 3: 2D/3D acquisition chain and processing for crime scenes or fictitious accidents

To check that the objects have been correctly detected, a documentation methodology similar to that used at a crime or accident scene has been defined.

In a real scene, different types of photographs are taken: general, close-up and detail.

Overall photographs are taken before and after the installation of the markers. Photographs done before the markers installation are particularly useful for viewing the scene with no previous entrance. This is because technicians or experts may inadvertently alter certain elements (position of furniture, objects, *etc.*) when they visit the site. As a result, photographs are often taken from the doorway without entering the scene, or, in the case of an outdoor scene, from the stage "entrance". In this project, these "doorway views" without markers will not be done. Overall photographs are taken to get a better idea of the scene at the beginning. These are generally photographs taken from the corners.

We then move progressively closer to take more detailed photographs but always respecting a certain continuity in the views. Before moving on to the next markers, it is necessary to have at least the previous marker in the same photograph. For example, if you have 3 markers named '1', '2' and '3' in a scene, if markers 1 and 2 are photographed close-up, when marker 3 is photographed: markers 1 and 2 must also be in view. The aim is to be able to find your way around the scene easily. Photographs from different points of view will be taken to better understand the scene.

We usually finish by taking detailed photographs of the features of interest, and in particular the traces and markers associated with them. For general, close-up and detailed photographs, see Figure 1, Figure 2 and Figure 5, respectively.

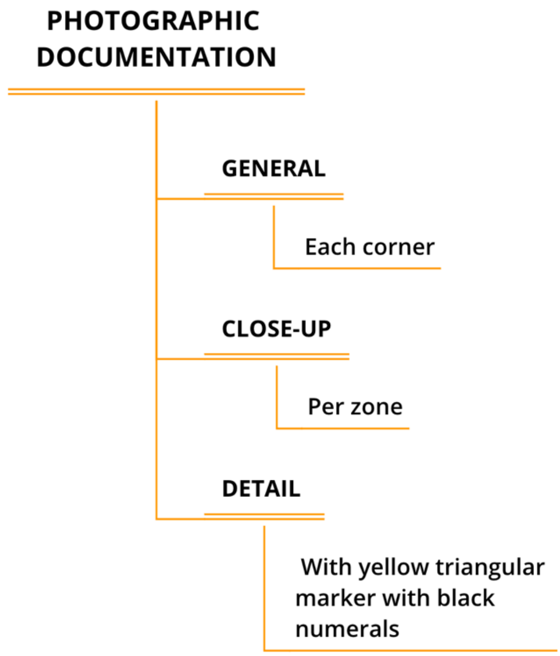

Figure 4: Photographic documentation for crime scenes or fictitious accidents

Depending on the country and the police force, a variety of sensors can be used, from SLR cameras with a variety of lenses (variable focal length or fixed focal length *eg.* for macroscopic photography always bearing in mind the need to minimize distortion as much as possible) to mobile phone sensors. To put ourselves in worst possible position to estimate the possibilities of detection using AI, we used a 13 Mp photographic sensor mounted in a 2016 CatS60 mobile phone.

Sensor	Resolution	Bandes	Format
Mounted on CatS60	3120 * 4160	RGB	.jpg

Table 4 : Scene documentation photo settings

This smartphone is also equipped with a FLIR thermal imaging camera. As the dummies simulating the bodies are not representative in terms of thermometry, this sensor will not be used.

In the context of fixing a real scene, 360° cameras may also be available. In our case study, when we carry out a 3D scan using the Faro Focus Premium laser scanner according to the parameters presented in Table 3, a planar view (360° view) in colour is generated. We will therefore not duplicate this step with acquisition using another sensor (*e.g.* a Ricoh theta camera).

Figure 5: Close-up view of part of scene Th_0002

We can see here that for each scene we have a large quantity of data which needs to be classified meticulously in order to make the best use of it. The data is therefore always labelled, starting with the number of the scene in question. The data is then named according to its characteristics.

The next step is to draw up an inventory of the evidence. This involves describing the evidence. The data entered is in fact attribute data which can then be used.

Inventory of exhibits	Marker number
11	5 white A4 sheets
12	15 red picks
13	4 white flex-studs
14	3 bottles of Metrop
15	Pump with 5 nozzles
16	4 white cans with blue caps
17	Blue Pen “bic”
18	2 white reflex ties
19	1 square key
20	1 handwritten A4 sheet "She wanted to leave me Adieu Vene pene plus Matthieu" with signature
21	Seated body in purple and pink tunic, hands tied with reflex ties, hands tied with cord and gagged with grey tape
32	Half-empty bottle of vodka
35	Plastic bag containing white seals
60	Black pen “bic”

Table 5: Spreadsheet showing part of the Exhibit Inventory for scene Th_0002.

An inventory of exhibits will be made for each scene.

4. Testing AI with forensic data

4.1 Machine learning

To begin with, in order to familiarise ourselves with the field of artificial intelligence and algorithms in Python, tests were carried out on the images in the documentation.

First to test algorithms in Python, index markers were searched using Ward's classification method (Scikitlearn, 2024). This is a hierarchical classification whose inertia between two classes (A and B), for example, is defined by the following formula according to (CNAM, 2008):

$$\sigma(A,B)= (P_A P_B)\, d^2(g_A,g_B) \,/\, (P_A+ P_B)\,, \qquad (1)$$

where g_A = centre of gravity of the class A (weight P_A)
g_B = centre of gravity of the class B (weight P_B)
$d(g_A,g_B)$: distance between the centers of gravity of classes A and B

Tests, coded in Python on the Jupyter development environment, were carried out on images from the fictitious scenes. Tests were also carried out on general images from the scenes, as well as on the 360° images exported by the 2D/3D acquisition chain (see Figure 3 - step Export).

In these codes, parameters were modified to see the effects on image processing. In particular, the number of regions to be taken into account during processing has been varied.

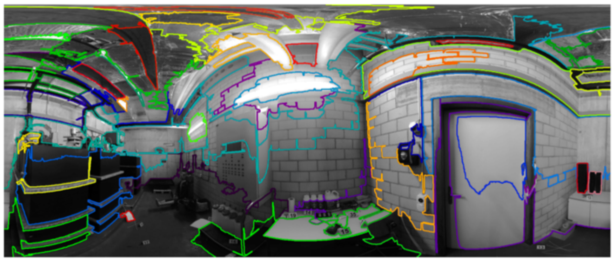

Figure 6: Ward’s classification results, number of regions: 50.

By varying the algorithmic parameters in Python, some markers have been detected. However, detection was not optimal. One way of improving results would be to use colourimetry, by performing calculations on both colour images and integrating the 'yellow' colour parameter in the marker search.

Overall, these tests proved interesting, but to make them more effective, certain algorithmic changes need to be made.

Secondly tests were also carried out in the field of machine learning using Python on the Jupyter development environment. The aim was to search for characters on markers (Scikitlearn, 2024), using a three-level neural network (input level, hidden level, output level). Indeed, as indicated in section 2.2, the numbering of index markers could prove fundamental as a primary key for the entire scene.

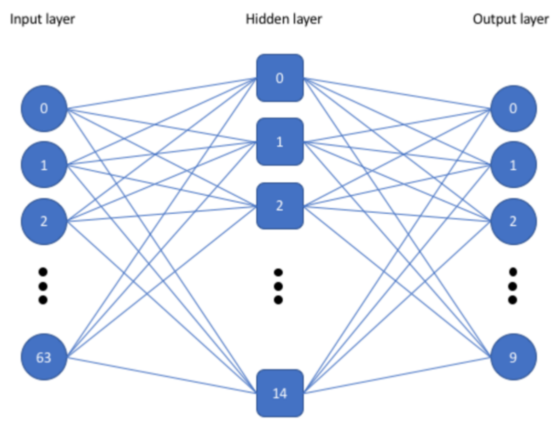

Figure 7: Three-level neural network, (Recognition_digit, 2024)

Therefore, to recognize characters (numbers), logistic regression, which is a classification method that predicts binary classes (sigmoid function), was used. This detection method worked well (detection of digits above 90%). It would be interesting to test this with fictional scene markers, for example.

Tests are underway, using image data from exercise scenes to find the numbering on the easels. This stage poses several difficulties: an easel does not only contain single-digit numbers, and the digits are not always perpendicular to the digital camera lens, which can lead to detection difficulties, for example. It will be necessary to integrate these particularities into the learning base so that they can be considered.

4.2 Deep Learning

Having carried out these tests, to gain a better understanding of the advances made by AI for data from forensic scenes, it became necessary to look at the processing of point clouds as described in paragraph 2.2. The aim is to be able to classify the elements of interest in the point clouds according to a forensic aspect.

During the literature review, one solution was found to be particularly interesting and suited to our case: the "SuperPoint Transformer" deep learning solution (Robert et al., 2023). To test this solution, a suitable Linux configuration had to be set up (Ubuntu 20.4 LTS, CUDA 12.1, Conda 23.3.1).

Before being able to use this solution, it was necessary to prepare a Python script in Jupyter to visualize the point clouds in accordance with the recommendations proposed by (Robert Environnement requirements, 2024). Initially, the point clouds from the digitized forensic scenes were exported in ".e57" format. To facilitate the coding of the visualization tool and the creation of a Data Object in Python, the clouds were exported a second time in ".las" format. Indeed, the time required to export all the point clouds was less than that required to modify the code to adapt the script to an ".e57" format, although this would have been possible. To speed up data processing, it is also possible to tile the point clouds. In our case, we didn't choose to divide the point clouds into a succession of tiles, as the latter are already small in size and this sub-division would add complexity to the data to be processed.

With this deep learning solution, it is possible to use a pre-trained model even if the class labels are not the same. In this case, we didn't make this choice and decided to train our own dataset.

We decided to divide our dataset into three parts: training data (30%), test data (40%) and confirmation data (30%). For the learning phase, 17 point clouds from fictitious scenes were used. For this phase, numerous trials were necessary to test the various pre-transformation and transformation parameters. These parameters were chosen by following the elements outlined by (Robert Environnement requirements, 2024) throughout the numerous processing steps: voxelization, neighbor search, elevation estimation, pointwise local geometric features, adjacency graph, hierarchical partition, superpoint-wise handcrafted features, superpoint adjacency graph and features. A final training dataset has just been obtained, and its characteristics now need to be verified before we can go any further with the deep learning processing.

5. Conclusion

This article has shown the informational links that exist within the framework of digital twins in forensic science. External data, but also the intrinsic information of the point cloud, are essential elements for better understanding and processing crime or accident scenes.

A test dataset of 57 fictitious crime or accident scenes was acquired. An acquisition methodology in terms of 3D scanning, documentation data (general, close-up and detailed photographs) and attribute data has been setup.

Algorithmic and machine learning solutions in Python language in the Jupyter development environment were tested. In particular, tests focused on the detection of markers using Ward's classification and on the detection of numerical characters on these same markers using the Sigmoid function (which could be used as a primary key for the entire scene). These tests have shown the potential of algorithms and of machine learning, using Python. However, to further improve detection, solutions based on colourimetry and better adaptation of training data could be implemented. Generally speaking, algorithmic and machine learning solutions do not require very advanced knowledge or complex configurations.

Initial deep learning tests have shown that the 3D data acquired can be visualized almost directly, provided that suitable export formats are chosen. Going a step further, to test the 'SuperPoint Transformer' deep learning solution (Robert SuperPoint Transformer, 2024), we can see that data integration is not as easy unless you have a dataset very close to a pre-trained one, which is not our case. Thus, it was necessary to configure numerous parameters for data pre-transformations. Multiple trials were necessary to create a training dataset. It seems, therefore, that this type of integration and processing by deep learning is not always self-evident. It is well known that the learning phase is certainly the most complex and important stage in deep learning processing. Indeed, the learning set will condition all subsequent processing.

Consequently, following initial tests, we need to continue these machine learning and deep learning operations to determine the relevance of these treatments in the field of forensics, and their consistency with the expected gains.

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