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TOWARD THE AUTOMATIC DEFLECTION ANALYSIS IN HISTORIC TIMBER SLABS BY COMBINING 3D POINT CLOUDS AND MACHINE LEARNING APROACHES

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ABSTRACT

In the field of Cultural Heritage, 3D point clouds have emerged as a key data source due to their ability to represent a scene (i.e., a timber floor or a complete building) with great resolution and accuracy (within a few millimetres) in a 3D digital space. While this data is commonly used for generating planimetries, HBIM and computational modelling; there is plenty of information within it that could extend its potential applications, particularly in the field of diagnostics.
Under this basis, this paper introduces a novel methodology that attempts to exploit the features contained in 3D point clouds with the aim of evaluating deflection in historic timber slabs. Towards this end we propose the combination of Artificial Intelligence approaches with other 3D point cloud methods to obtain relative deflection in timber beams with great accuracy and automatization. More specifically, we propose a multi-resolution and multi-stage Random Forest classifier to detect the beams as well as its faces. These elements are further processed with the aim of extracting the relative deflection by using the connected component and minimum bounding rectangle algorithms.
This methodology has been applied to a real study case with deflected timber slabs. Specifically, several floors of the Nuestra Señora convent in Avila were examined. The results obtained are really promising, showing a high level of accuracy in element detection (99% overall accuracy achieved by the Random Forest classifier) as well as a high degree of automatization.

KEYWORDS

Diagnostics, Laser scanner, Artificial Intelligence, Timber floors, Point Cloud

1 INTRODUCTION

3D point clouds have gained substantial recognition within the construction industry as an invaluable source of information. These point clouds find diverse applications such as 3D model reconstruction, safety management, building performance analysis, and construction progress tracking [1], [2].
A 3D point cloud is essentially a collection of data points within a 3D coordinate system, meticulously representing the surfaces of objects or environments. This versatility is made possible by the capacity of 3D point clouds to accurately represent the geometric characteristics of Cultural Heritage objects, including their dimensions, shapes, orientations, and positions. Within this field, point clouds find practical uses as the geometrical base for generating models for Historic Building Information Models, computational analysis, and the creation of built planimetries [3].

Moreover, this use could be extended to the field of damage detection, particularly when exploiting the geometric and radiometric features of the captured data [4].
This question is highlighted in the recent literature review conducted by Sánchez-Aparicio et al. [3], showing the great potentiality of this information source in detecting deformations, settlements, moisture areas or crusts among other forms of damage. Examples of this potential can be found in the works performed by Sánchez-Aparicio et al. [4], Valero et al. [5] or Masiero and Costantino [6].

In contrast to the promising potential offered by feature analysis, the methodologies for damage detection currently require manual segmentation of the constructive elements to be carried out [3]. This issue has been identified as an area of potential future research in the literature review performed by Sánchez-Aparicio et al. [3]. Within this context we can find in the recent literature a plethora of studies that have addressed the constructive segmentation of 3D point clouds

by employing Artificial Intelligence approaches [7]. A notable example of this capacity can be found in the study performed by Teruggi et al. [8] the Milan Cathedral. In this work the authors propose the use of a Machine Learning algorithm (i.e., Random Forest classifier) to split the 3D point cloud into constructive elements. The results of this work are highly promising, as the methodology performs with remarkable accuracy, even in complex environments like the Cathedral.
Taking in consideration the current state of the art, the aim of this work is to develop a method capable of integrating Artificial Intelligence approaches for constructive segmentation and geometric-based methods for the automatic evaluation of deflections in historic timber floors. To validate the proposed strategy, the interior of the convent of Nuestra Señora de Gracia in Ávila (Spain) was chosen as a study case.

In this context, the paper is structured as follows: Section 2 defines the materials and methods used in this work, including the study case; Section 3 presents the results achieved through the application of the proposed methodology and, finally, Section 4 summarises the conclusions drawn from this research, along with further lines of work.

2 MATERIALS AND METHODS

2.1 STUDY CASE

The chosen case study is Nuestra Señora de Gracia convent in Avila, Spain. This historical architectural complex has been preserved since the 16th century and has undergone various modifications up to the 20th century. The construction follows a "U" shape layout, carefully adapted to the natural landscape. The building comprises load-bearing masonry walls and wooden floors, which are directly supported by the ground, except for one corridor that features arched brick galleries. For further details about the constructive disposition of this building the reader is encouraged to consult Villanueva-Llauradó et al. 2022 (Figure 1) [9].

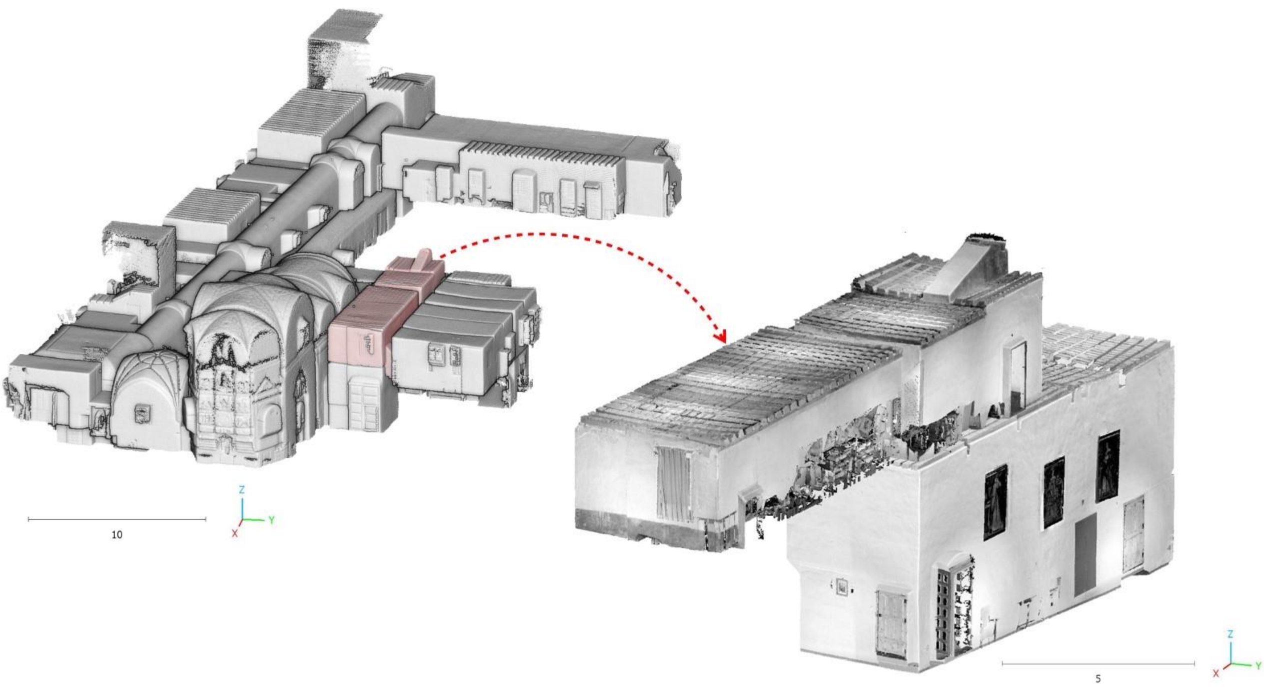


Figure 1. 3*D point cloud of the convent Nuestra Señora de Gracia. The red zone highlights the area of interest for this study Adapted from Villanueva-Llauradó et al. 2022* [9], [10].

The data employed in this study was extracted from a previous digitalization campaign in which part of the timber slabs were digitalized through the application of the terrestrial laser scanner Faro Focus 120 (Figure 1, 2) [9]. This LiDAR sensor employs the Amplitude Modulated Continuous Wave (AMCW) measurement principle, known for its high data acquisition rate and accuracy. Specifically, this sensor is capable of capturing between 120,000 to 976,000 points per second with a nominal accuracy of 2 mm.

Figure 2. *Slabs of the convent Nuestra Señora de Gracia*

2.2 METODOLOGY FOR EVALUATING THE DEFLECTION OF THE BEAMS

As it was previously outlined in the introduction, the primary objective of this research is to develop a methodology capable of exploiting the information contained in the 3D point cloud by combining Artificial Intelligence techniques with other point cloud processing methods. This methodology is summarized in the Figure 3.

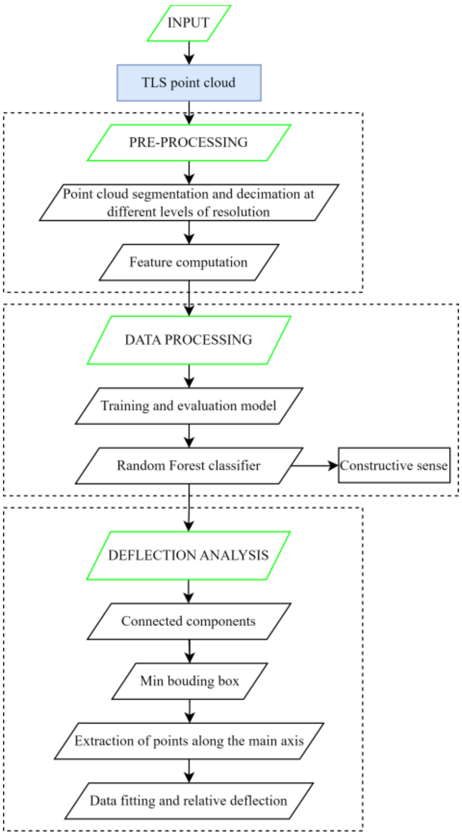


Figure 3. *Scheme of the proposed workflow*

The input of the methodology is the 3D point cloud acquired through Terrestrial Laser Scanner. This point cloud is a compilation of data from multiple scan stations that were aligned into a unique coordinate system. This input is pre-processed with the purpose of deleting extraneous elements such as people or ornamental motifs that were captured during the digitalization campaign. This phase also encompasses a sampling step to ensure uniform data density in the input. After that, a data processing stage is proposed. This stage includes features extraction (used at the Artificial Intelligence training) as well as the classification of the data employing a Random Forest strategy. Finally, the methodology includes a defection analysis on which it uses the data extracted from the previous stage as well as several point cloud processing algorithms to autonomously extract the defection of the beams.

2.3 DATA PRE-PROCESSING

The initial step involves the preparation of the 3D point cloud for Artificial Intelligence segmentation. To this end, it is required to apply the following stages: i) removal of non-relevant areas; ii) subsampling and ii) data classification. All these operations were carried out with the open-source software CloudCompare® (https://www.danielgm.net/cc/). During the first stage, we decided to eliminate ornamental elements, furniture and any people captured during the data acquisition process. Subsequently, we conducted the subsampling and classification of the 3D point cloud. Both stages are mandatory in order to fulfil the final goal. The subsampling serves to homogenize the input data, while data classification provides semantics to the 3D point cloud, making it suitable for training and testing the Artificial Intelligence. They were implemented following the approach proposed by Teruggi et al. [8]. In this article the authors introduce a multi-level and multi-resolution subsampling and classification technique in contrast to the traditional on-step training, which has been proven to enhance the efficacy of the Artificial Intelligence model.

The first level refers to the main structural framework of the different rooms within the convent, defining a global functional segmentation of the entire dataset; categorizing it into floors, vertical walls and slabs. These macrocategories were achieved through point cloud processing at a 5cm resolution.
The second level introduces a deeper definition by breaking down the macrocategories from the first level. In this case, the floor is divided into joists and wooden boards with a higher resolution level of 2 cm.
Finally, the third level involves the subcategorization of the previous level with a resolution of 1 cm. Therefore, the timber joists are subdivided into their scanned views, distinguishing between the base and sides of the joists. This detailed categorization will be useful for automatic joist deflection extraction.
It is worth noting that for training purposes, only classifying 25% of the entire scene is required [7]. However, in the context of this study we made the choice to classify the entire scene within various resolution levels in order to assess the performance of the algorithm (Figure 4, 5, 6).

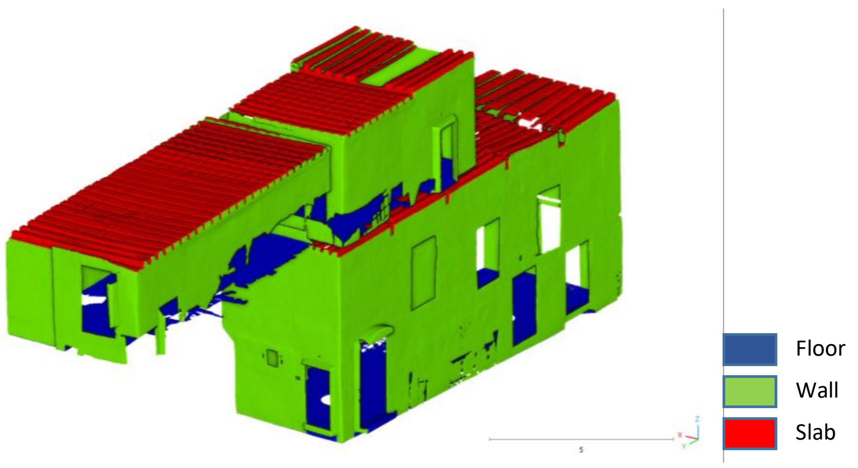


Figure 4. *3D point cloud segmented on first level of classification*

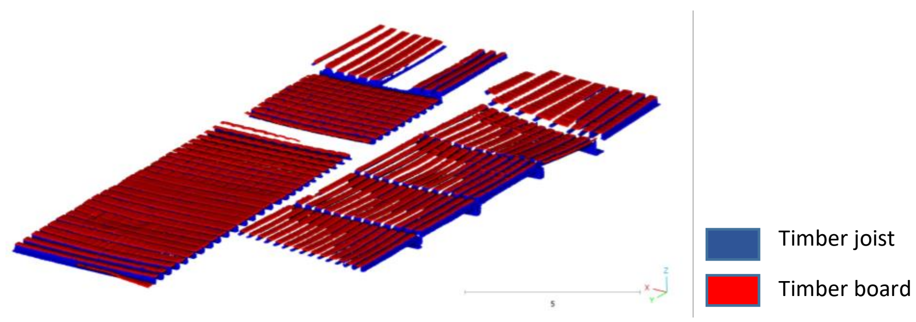


Figure 5. *3D point cloud segmented on second level of classification*

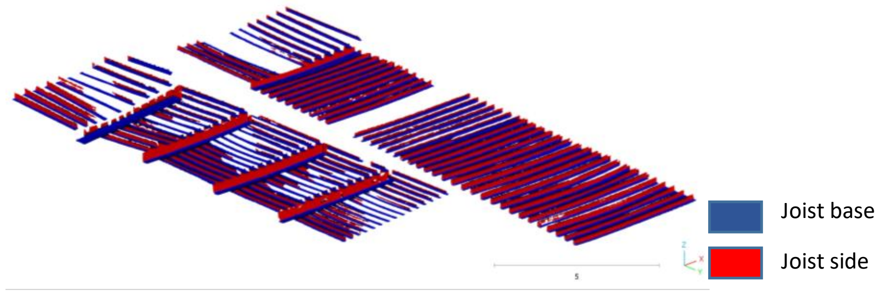


Figure 6. *3D point cloud segmented on third level of classification*

2.4 DATA PROCESSING

Artificial Intelligence Training can be understood as a process in which a model establishes a relationship between specific inputs (i.e., coordinates or features of the points) and the corresponding class assigned to each point. This process requires to perform a multistage workflow, which can be summarized as follows: i) the feature extraction; ii) the train-evaluation splitting and iii) the classification.

2.4.1 Feature extraction

Feature extraction in the context of a 3D point cloud involves the process of adding new layers of information (features) to each point within the point cloud defining their local characteristics. The following parameters were used in this study: i) geometric features (Roughness, mean curvature, gaussian curvature, normal change rate, sum of eigenvalues, omnivariance, eigenentropy, anisotropy, planarity, linearity, surface variation, sphericity and verticality) applying the feature equations defined in the work by Weinmann et al. [11], ii) the Z parameter, which differentiates the point cloud according to its location along the Z axis, iii) the relative position parameter, which divides the point cloud according to the laser scanner's height (points above a certain height are assigned a value of 1, while points below are given a value of 0), and finally iv) the intensity parameter, which differentiates the point cloud according to its degree of intensity. It is worth noting that the feature extraction process requires the definition of an appropriate neighbour's size. In this case a search radius (Figure 7) was employed with different range values assigned to each analysis level. Specifically, 0.1 to 1.6 meters for Level 1, 0.05 to 0.8 for Level 2 and 0.025 to 0.4 for Level 3.

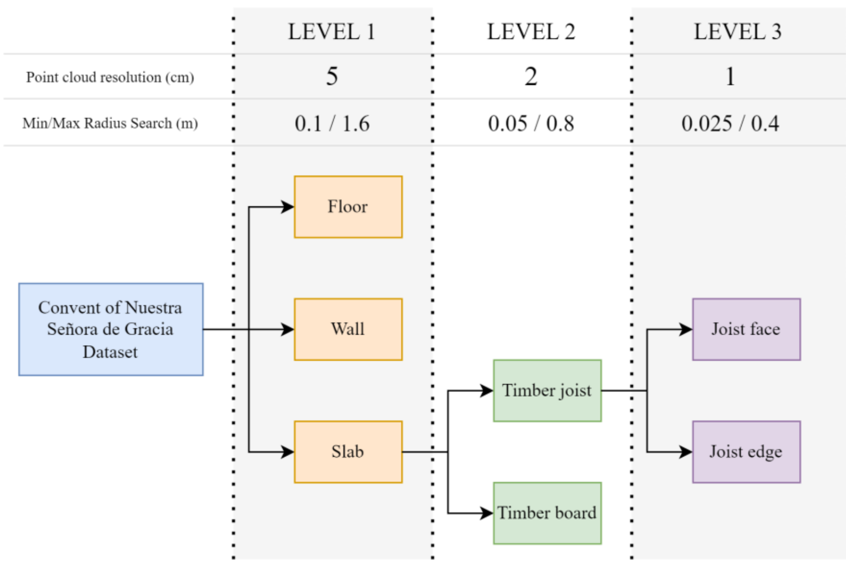


Figure 7. *Scheme of the methodology used for classification*

2.4.2 Training and evaluation

In addition to extracting the geometrical features, a subset of the point cloud was manually divided to train the Artificial Intelligence algorithm at each classification level. In this study, less than 25% was allocated for the training model; while the remainder served to evaluate the algorithm's performance.
The Figure 8 displays the training segment of the point cloud (colored) in comparison to the evaluation part (grey).

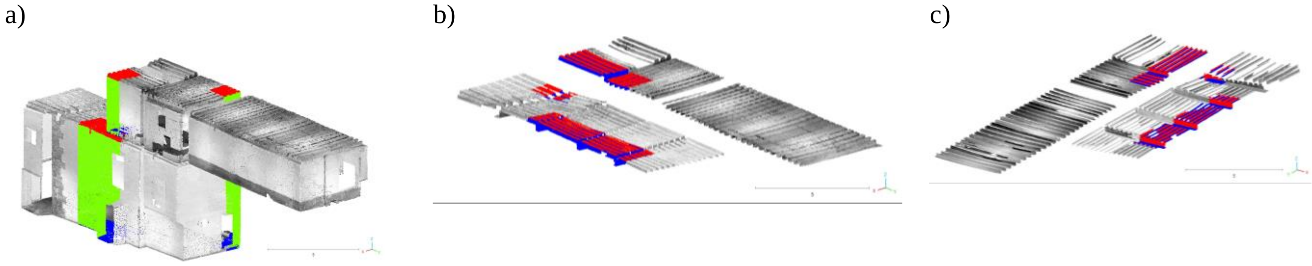


Figure 8. Train-evaluation splitting: a) level 1, b) level 2 and c) level 3

2.4.3 Random Forest classification method

The final step of this stage comprises the automatic classification of the point cloud. To this end we opted to employ a Machine Learning approach, specifically the Random Forest algorithm [12]. This algorithm is highly used in the literature as evidenced by the review performed by Yang et al. [7]. This method combines multiple decision trees to perform an accurate classification of input data. Its ability to handle complex and noisy datasets, as well as its resistance to overfitting, makes it a solid choice for this classification task.
In the present work, Python® scripts have been used to run the Random Forest, more specifically we use the library scikit-learn (https://scikit-learn.org/stable/index.html). The count values for both accurate and erroneous predictions are condensed and presented within a confusion matrix, a specialized tabular format designed for visualizing the algorithm's performance. Within this matrix, individual rows correspond to predicted class instances, while each column corresponds to actual class instances. Moving on from the confusion matrix, we utilize three key metrics for each class: i) Precision, which gauges the level of precision or correctness, ii) recall, which evaluates the degree of comprehensiveness or completeness and iii) the F1-score, which harmonizes both precision and recall into a single metric. These strategies are commonly used in this type of works [8].

2.4.4 Deflection analysis

The previous stage enabled us to give semantic to the 3D point cloud, facilitating its division into areas of interest, such as the bases of the joists. These bases comprise a set of points that can be processed to accurately determine the current deflection of these elements. To this end the following algorithms were applied (Figure 9): i) the connected components strategy; and ii) the minimum bounding rectangle approach.
The first of the algorithms allow us to segment the class "joist edge" into individual elements. To this end the algorithm splits the 3D point cloud into 3D voxels with a predefined dimension. Then, the algorithm evaluates the connectivity of each voxel with its neighbours, allowing to split the 3D point cloud into elements that are separated by a specific distance.
At this stage of the process, we have extracted several 3D point clouds from the original one, each representing a joist edge. It is worth noting that from a geometrical point of view, the 2D projection of these edges can be represented as rectangles. Under this assumption, we decided to project the 3D point clouds of each joist onto the X-Y plane and subsequently apply the minimum bounding rectangle algorithm. This method enables the determination of the rectangle with the minimum area from a set of 2D points (x, y coordinates of the edges), whose main axis correspond with the desired axis of the joist.
The final step of this stage comprises the extraction of the deflection. In this sense, it is necessary to determine the length of the beam (length of the minimum bounding rectangle) as well as the maximum and minimum deflection (z-coordinate). The latter is only computed on those points that fall within a tolerance range from the main axis to enhance the process efficiency.
The first step was performed in the open-source software CloudCompare ®. Meanwhile the rest were computed by using an in-house Python script. Thanks to the data extracted, it becomes possible to compute the relative deflection (maximum drop of span with respect to the end of the part with the smallest span, divided by the span of the section) of each joist in accordance with Spanish guidelines for timber structures [13].

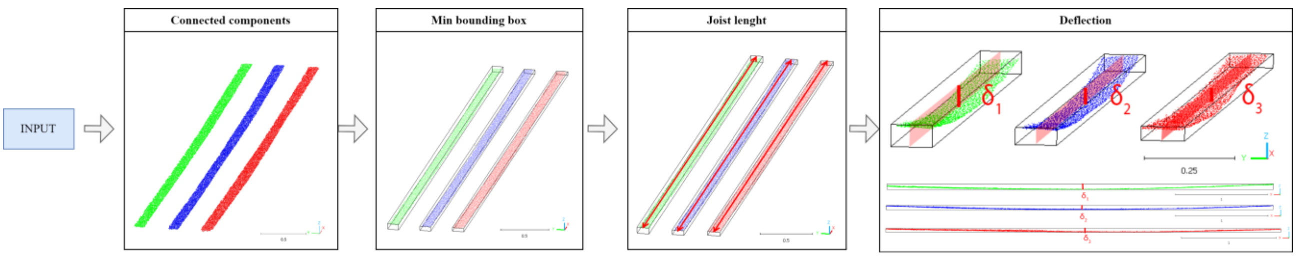


Figure 9. Scheme of the proposed deflection analysis

3 EXPERIMENTAL RESULTS

The following section will show, step-by-step, the results obtained in each one of the stages previously described.

3.1 PRE-PROCESSING OF THE 3D POINT CLOUD

Firstly, we remove elements that are not contextually relevant, such as decorative motifs or individuals. Then, the 3D point cloud is subsampled at different resolution levels in accordance with Section 2.3.1. Finally, we extract the features of the 3D point cloud using the point cloud processing software CloudCompare® (https://www.danielgm.net/cc/). The following figures show part of the results obtained during the feature computation stage.

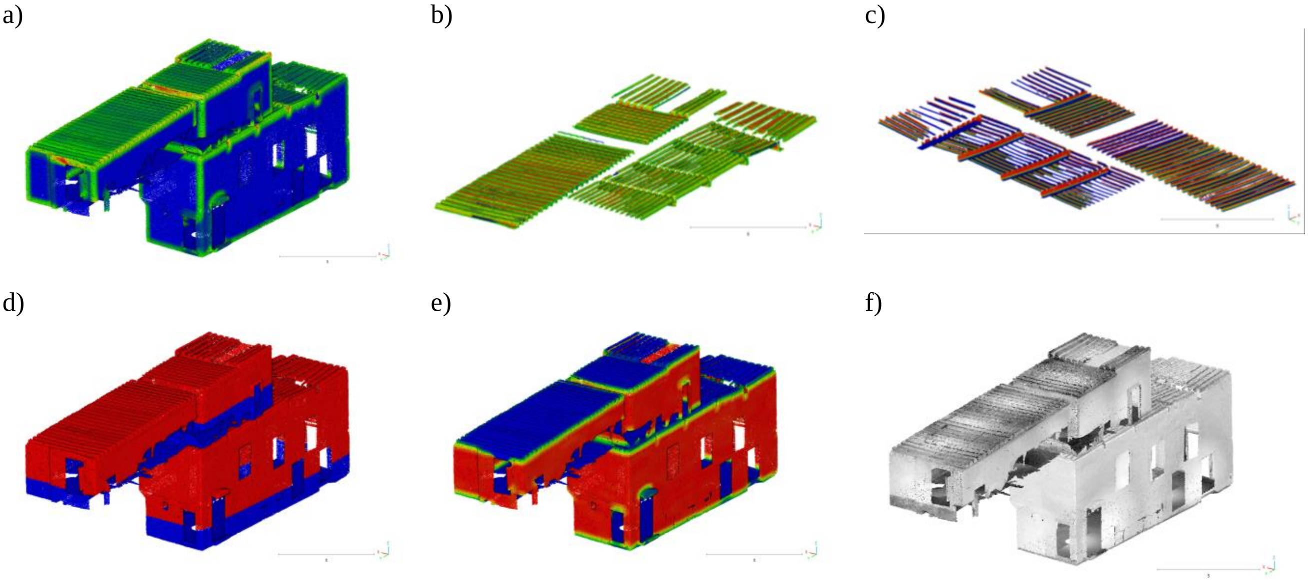


Figure 10 *Feature computation results: a) Level 1 (Surface variation 0.4), b) Level 2 (Planarity 0.1), c) Level 3 (Verticality 0.05), d) Relative position, e) Verticality (1.6) f) Intensity*

3.2 MACHINE LEARNING PREDICTIONS

As mentioned above, Random Forest has been performed on each level of the 3D point cloud, employing the enriched 3D point cloud as input (with the features previous showed). This step was carried out by using an ad-hoc script written in Python. The parameters used to run the Random Forest script were i) number of estimators (100,200), ii) maximum deep (none), iii) maximum number of features to take (square root), iv) bootstrap (false, true); as well as graphs to show results: i) Importance, ii) confusion matrix and iii) matrix classification matrix. The following tables and figures show the outcomes obtained during the application of the machine learning approach at various levels (Figures 11, 12, 13, 14 and Tables 1, 2, 3).

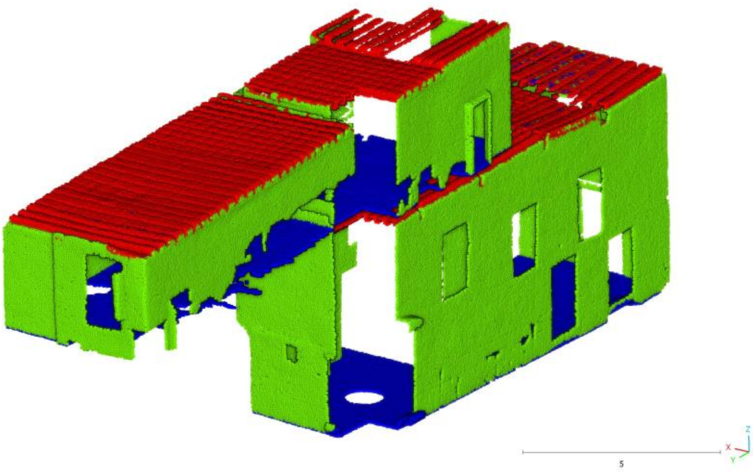


Figure 11. *3D point cloud of the prediction on first level of classification*

Table 1. *Classification metrics at level 1*

	Precision (%)	Recall (%)	F1 Score (%)
Floor	98.4	99.9	99.1

Wall	99.2	98.4	98.8
Slab	97.8	98.1	97.9
Macro average (%)	98.5	98.8	98.6
Weighted average (%)	98.6	98.6	98.6

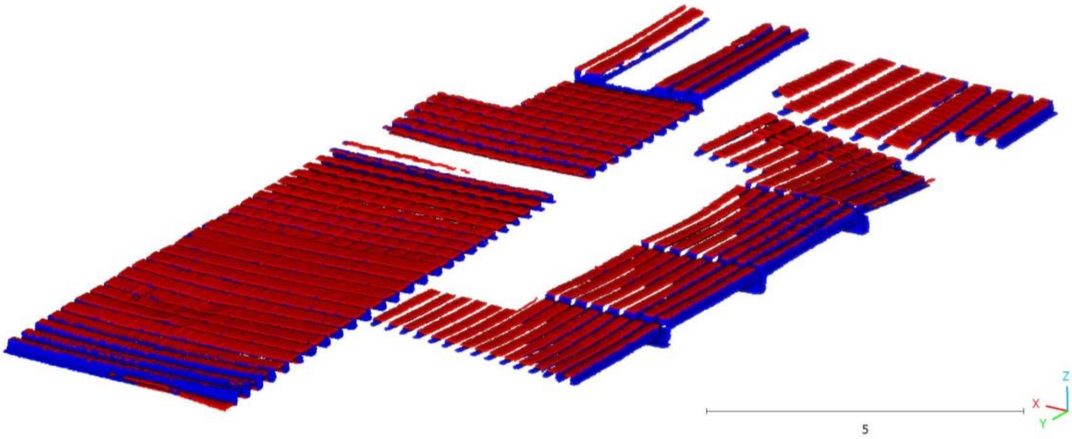


Figure 12. *3D point cloud of the prediction on second level of classification*

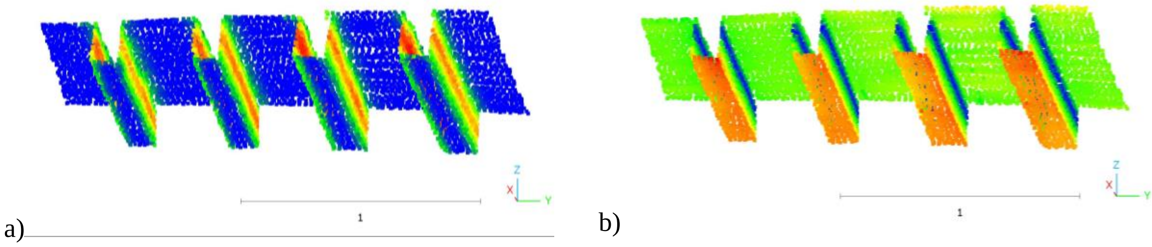


Figure 13. *Features with great impact (importance) in the final classification: a) Verticality (0.1), b) Roughness (0.4)*

Table 2. *Classification metrics at level 2*

	Precision (%)	Recall (%)	F1 Score (%)
Timber joist	97.9	97.9	97.9
Timber deck	97.4	97.5	97.4
Macro average (%)	97.7	97.7	97.7
Weighted average (%)	97.7	97.7	97.7

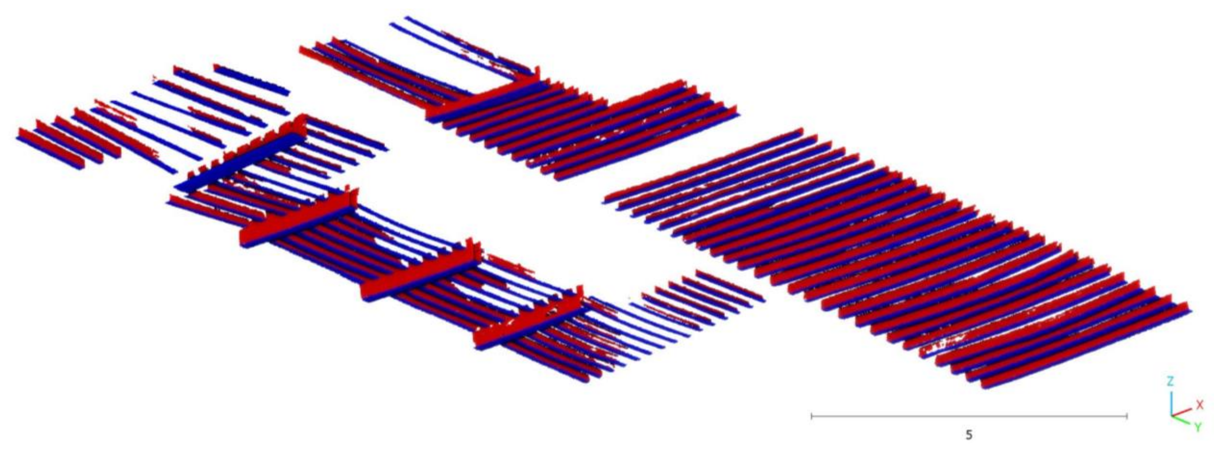


Figure 14. *3D point cloud of the prediction on third level of classification*

Table 3. *Classification metrics at level 3*

	Precision (%)	Recall (%)	F1 Score (%)
Joist edge	99.2	99.0	99.1
Joist face	99.3	99.4	99.4
Macro average (%)	99.2	99.2	99.2
Weighted average (%)	99.3	99.3	99.3

During each classification the impact of each feature on the results was analysed. To this end, we decided to use the Feature Importance graph, ranking the features in accordance with their impact on the results. This impact was measured by using the Giny purity index [12]. The following figure shows the results of this analysis.

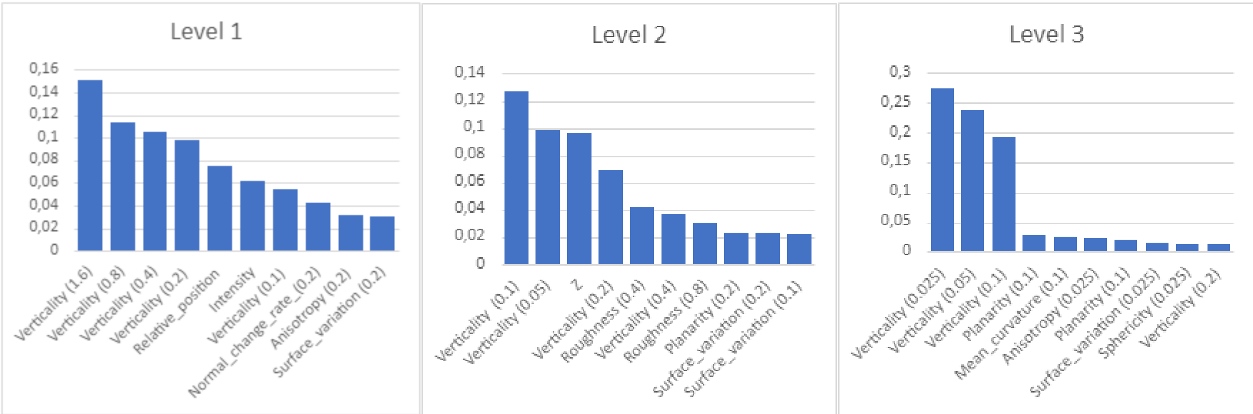


Figure 15. *Feature importance results: a) Level 1, b) Level 2 and c) Level 3*

From this figure we can highlight the relevance of the verticality (at different levels), the Z coordinate, and the relative position as well as the intensity of the laser scanner (Figure 16).

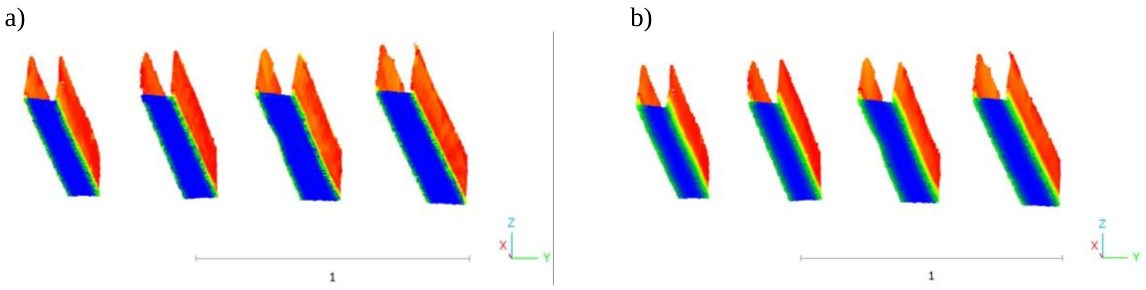


Figure 16. *3D point cloud of the best parameters for the Random Forest: a) Verticality (0.025), b) Verticality (0.05)*

According with the evaluation metrics, the performance of the Random Forest classifier is close to perfection, showing minor mismatches in areas with great difficulty (i.e., beam attached to the wall) or regions with low data density (Figure 17). These mismatches required manually correction to ensure the proper deflection analysis of the beams.

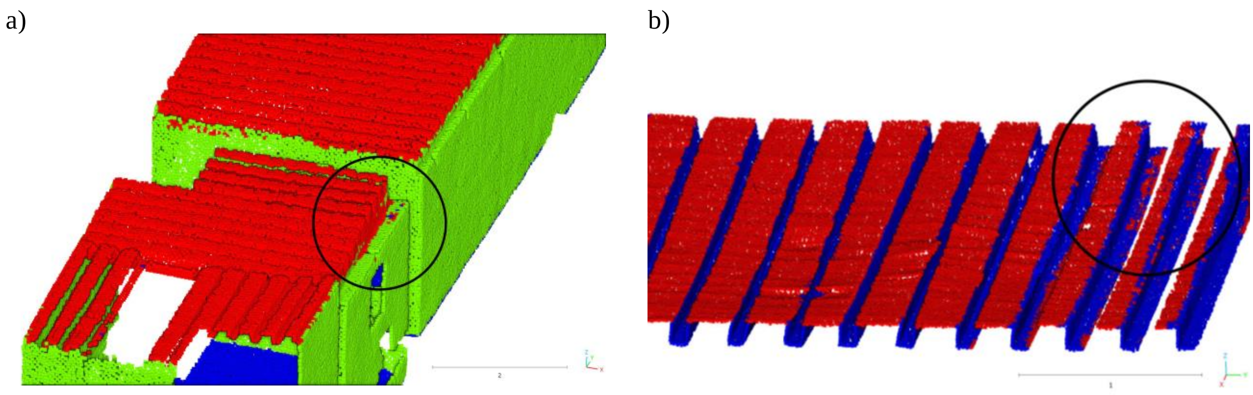


Figure 17. *Mismatches of the Random Forest classification: a) Level 1, b) Level 2*

3.3 CONSTRUCTIVE MEANING OF THE RESULTS OBTAINED

The results of the feature importance analysis provide a general overview of the relevance of each feature (Figure 15). To summarise, the best parameters for classification were: i) the geometric features for all levels, in particular the verticality parameter, ii) the Z parameter for level 2, iii) the relative position for level 1 and iv) the intensity for level 1. This significance appears to be linked with certain constructive aspects of this type of slabs [14] (Table 4,5).

Table 4. *Relation between the search radii and the standard measurement. Information obtained from (Lasheras et al. 2009)*

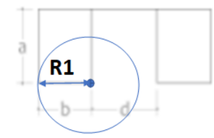
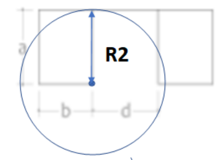
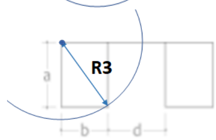
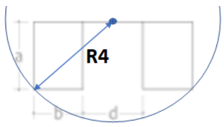
Joists section detail and their respective search radii	Formula	Standard length (mm)
	$R1 = b$	104
	$R2 = a$	139
	$R3 = \sqrt{(a^2 + b^2)}$	173,6
	$R4 = \sqrt{\left(a^2 + \left(\frac{b+d}{2}\right)^2\right)}$	267,9

Table 5. *Justification of the best parameters*

	Level 1	Level 2	Level 3
Geometrical Features	The Scalar Verticality is the best result, especially with radius 1.6, which determines the completely horizontal slab construction system. According to the radius calculations, verticality should be completely disregarded for floor slabs with a radius greater than 0.268 mm, i.e., if it is greater than R4.	The best result is obtained with the smallest radius for Scalar Verticality, since a larger radius means less distinction between the horizontal and vertical planes that make up the slab. According to the radius calculations, to differentiate the joist from the deck, the radius should be smaller than R3, i.e., less than 173.6 mm. A greater radius would mean that no point on the joist would recognise any other point on the joist within the same plane perpendicular to the joist.	The best result is obtained with the Scalar Verticality with a smaller radius, as a larger radius means less distinction between the vertical and horizontal plane that forms the joist.
Z parameter	It leads to confusion between the floor of the upper storey and the slab below, as the two are very close together (15/25 cm).	This parameter improves the prediction because the deck is above the joist.	This parameter does not improve the prediction because the joists have an excessive deflection (subsequently calculated), which implies that many points of one class are in the same Z position as the other.
Relative position	More accurate than Z parameter, as it differentiates the floor from the slab into two distinct classes.	It is disregarded since the entire point cloud of level 2 is above the scanner.	The same as in the Level 2.
Intensity	This parameter obtains better results as all building systems are made of different materials.	As both construction systems are made of the same material, this parameter does not improve the result.	The same as in the Level 2.

3.4 TIMBER JOISTS DEFLECTION

The final stage of the methodology comprised the calculation of the beam´s deflection. For this purpose, we employed the "Joist edge" class as input. This stage was computed by using an ad-hoc Python script following the steps defined in Figure 9. First, we split the beams by using the Connected Component algorithm. In this case the unique input value was the voxel resolution set at 1 cm, enabling the proper separation of elements (Figure 18).

a) b)

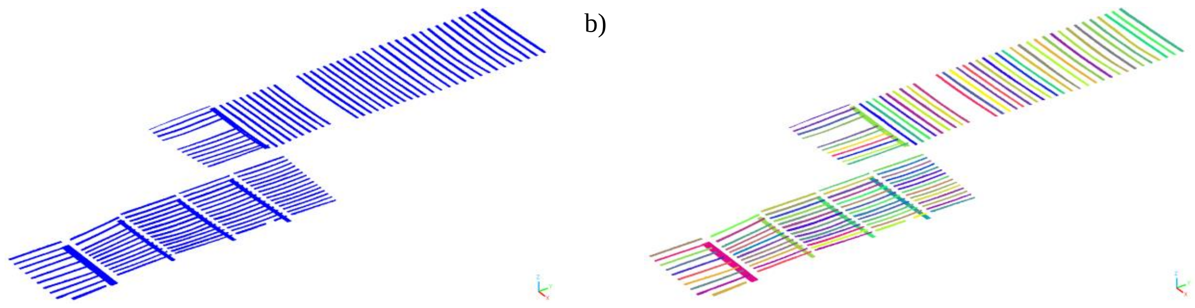


Figure 18. *Results after applying the first step: a) original input; b) element clusterization by using the connected components algorithm.*

Following this, we computed the minimum bounding rectangle for each beam to determine its main axis and calculate its length. Complementary to this value, the length, we extracted the maximum and minimum height within each beam. These values were plotted in a single graph with the aim of facilitating further structural works (Figure 19).

a) b)

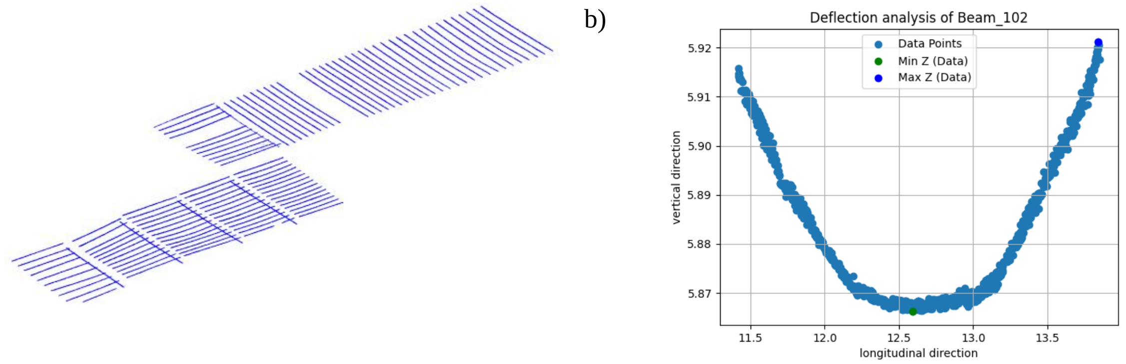


Figure 19. *Results after applying the second step: a) extraction of the beam axis by using the Minimum Bounding Rectangle algorithm; b) example of the graph obtained in the beam number 112 (units expressed in metres).*

To enhance the workflow of the inspector, the results of this deflection analysis were integrated into the original 3D point cloud by adding two new layers. One layer represents the maximum deflection on each beam, while the other layer plots the beams that fulfil the relative deflection (L/300) threshold in green and those that do not meet the requirements in red (Figure 20).

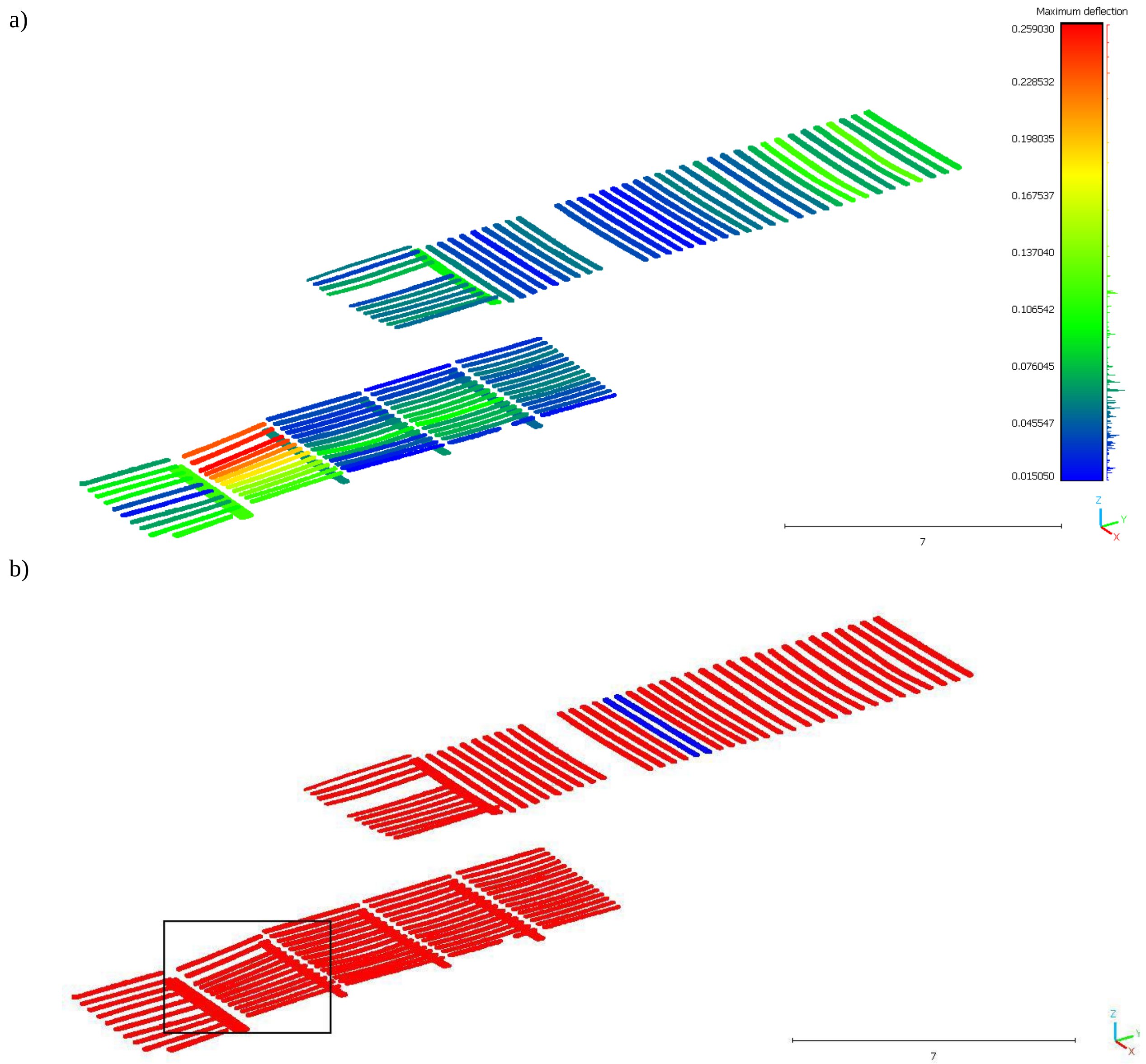


Figure 20. *Results of the final 3D point cloud: a) with the maximum deflection layer (difference between the highest and the lowest point); b) with a layer that represents in blue the beams which meet the relative deflection (L/300) threshold and in red those that don't fulfil this requirement.*

It is possible to observe that most of the beams do not meet the relative threshold requirements. However, there are some beams for which deflection is not properly calculated due to their lack of perfectly horizontal alignment (Figure 20 b). This aspect has been identified as a limitation of the current approach, as the deflection (L/300) in those beams can no longer be calculated because it would correspond to an end instead of the centre of the beam.

4 DISCUSSION OF THE RESULTS

This paper aims to present a methodology for the automatic evaluation of deflection in historic timber slabs. This methodology integrates Artificial Intelligence approaches for element segmentation and geometric-based methods for deflection parameters extraction.

On one hand, the results for element segmentation are highly promising, with accuracy values near to 100%. However, there are some classification mismatches that seem to be related to lack of data during the acquisition process, requiring manual fixing. In terms of processing time, we observe that the methodology performs efficiently (Table 6), running in just a couple of minutes on a system equipped with an i7 core processor, 16 Gb of RAM and a Graphical Computer Unit NVIDIA RTX A1000 6GB Laptop GPU. The most time-consuming stage is feature computation, as it involves extracting neighbourhood as well as geometric features (single value matrix analysis) for each point within various search radii, especially at higher levels of resolution.

Table 6. *Processing time*

Processing steps	Level 1	Level 2	Level 3
Subsampling (sec)	1	2	2
Feature computation (sec)	42	79	143
Exporting as .xyz (sec)	2	4	9
Random Forest (sec)	9	34	57
Joist deflection (sec)	-	-	60
Total (sec)	54	119	271

On the other hand, the geometric-based methods used for extracting the deflections of the slabs allow us to obtain the parameters of great interest, such as the length of each beam and its deflection. In this case, the process required just only 60 seconds to perform the analysis of 116 beams. However, we have identified two limitations that need improvement in future research: i) the need for perfect classification of construction systems to perform in optimal conditions; and ii) the necessity of improving the deflection calculation in the case of non-horizontal beams. In this regard, minimal user intervention may be required to verify the accuracy of the results.

5 CONCLUSIONS AND FUTURE WORKS

In accordance with the previous sections, it can be concluded that the proposed methodology shows a great potential for diagnosing timber slab floors as it seems to be robust and fast. However, it should be noted that this methodology is not entirely automatic due to the mismatches that could appear during the Random Forest classification. These mismatches are typically associated with areas lacking data density and points. Therefore, effective data acquisition planning is essential to minimize these issues, including minimizing the presence of out-of-context elements since they require manual segmentation before applying the classifier. In terms of time efficiency, this methodology can save a substantial amount of time compared to manually measuring deflections, requiring just a few minutes to process the slabs used in this study.

Future works will focus on the following fields: i) further validation; ii) extension to other timber structures: iii) development of a tool able to integrate the process shown in this paper.

Regarding the first one, we have planned to apply this methodology to other study cases where a deflection analysis of timber structures is necessary. This will help to assess the replicability of the method.

Apart from this, it is required to extend this methodology to a wider range of timber elements, such as roof systems consisting of inclined rafters and trusses. In this sense, the incorporation of the Principal Component Analysis algorithm will be required to transition from inclined bases to horizontal ones and, consequently, implement the stages defined in the deflection analysis.

Finally, we have planned to develop an open-source tool that integrates this workflow within a unique software platform to make it more user friendly. To this end we intend to develop a plugin for the open-source software CloudCompare® by utilizing a Python® wrapper for CloudCompare® (https://github.com/tmontaigu/CloudCompare-PythonPlugin)

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