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A point cloud classification method for the ScanToBIM process in Architectural Heritage

Heritage Building Information Modelling (H-BIM) has completely changed the meaning of managing architectural sites and ancient buildings. Nowadays, the application of cutting-edge methods for analysis, conservation and restoration is made possible by the modern 3D scanning technologies, such as terrestrial laser scanners (TLS) and digital cameras, which produce highly accurate point clouds. Furthermore, as these files are time-consuming and computationally expensive, strategies are being developed to optimise their handling and to streamline the conversion of a point cloud into a BIM model, adopting Scan-to-BIM approaches and widespread Artificial intelligence. In this scenario, the current work investigates the use of the CANUPO multiscale algorithm and the RANSAC model-fitting method for the classification of the staircase of Palazzo Nico, a neoclassical building in Gioia del Colle, Italy, using data obtained through TLS. The location's geometry, which includes numerous floors, vaults, balustrades, and typical 19th-century-style ornate staircase, makes it an excellent case study for assessing the applicability of these tools, serving as a source base for additional modelling procedures.

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Keywords:
TLS; Point cloud; Classification; Segmentation; Scan to BIM; H-BIM

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INTRODUCTION AND BACKGROUND

Point clouds are the end product of the accurate gathering of three-dimensional data made possible by Light Detection and Ranging (LiDAR) technology (X. Wang et al., 2020) or by Close Range Photogrammetry (CRP) (Aicardi et al., 2018), even with complementary use (Di Giulio et al., 2017; Hassan & Fritsch, 2019).
With the Scan to BIM procedure (Maiezza, 2019), which employs 3D data to collect the current building information and to have a metric reference in case of model construction (Badenko et al., 2019; Rocha et al., 2020), scan data is converted to BIM models. However, raw source data are frequently challenging to process, especially when you have scans that are extremely dense and contain billions of points. As a result, it is possible to perform point cloud processing and optimisation operations (Haznedar et al., 2023) in a way that makes it computationally manageable and supports the subsequent modelling steps (Adekunle et al., 2022; Ozdemir & Remondino, 2018).
To maintain the crucial points that are necessary for the recognition of shapes and their 2D generators polylines, the point cloud simplification should consider the three-dimensional generation processes to it will be subjected for BIM authoring. In the Scan-to-BIM process, this approach may be useful to provide a decomposition of the entire point cloud into regions of points, based on Homogeneous Spatial Scopes (ASO) or Homogeneous Functional Scopes (AFO) type decomposition criteria, according to the UNI11337 and UNI EN ISO 19650 technical standards.
There are several types of "compression" and "simplification" methods based on different approaches: compression methods are aimed at reducing the volume of data by analysing the spatial correlation of points (Schwarz et al., 2019); the other techniques are based on eliminating of redundant points or those considered "useless" for processing purposes, while attempting to preserve points that define characterising information or shapes (Pauly et al., 2002). In the latter group of algorithms, we can identify two macro-categories: the ones that directly perform an analysis on the points and the others that rely on 3D mesh reconstruction processes to identify redundant surfaces (Marais et al., 2019). There are additional method options that differ according to the properties considered in the computation: some rely on the identification of the deleted points using a spatial subdivision process (Spatial Division-based); others use a streamlined cloud reconstruction depending on the normal properties of the points (Huang et al., 2013); and still others that use the analysis of characterising parameters in order to determine the significance associated to the point and ensure the recognition of the detected shapes (Gong et al., 2021; Ji et al., 2019; Leal et al., 2021).
In the Cultural Heritage (CH) domain, also multiple methods for segmenting and classifying points clouds are increasingly being developed (Grilli et al., 2017) to denote a semantic meaning for different regions of the cloud itself, for instance by separating specific objects or elements, such as walls, floors, ceilings, columns, windows, and doors. The goal is to organise the data in a way that makes it simple to extract, edit, and use it to build BIM models. The most popular and contemporary segmentation methodologies focus on the approaches "region growing", "model fitting" and "unsupervised clustering", "Machine Learning" (ML) and "Deep Learning" (DL) (Goyal et al., 2021; S. Yang et al., 2023). The CAractérisation de NUages de POints (CANUPO) multiscale algorithm (Brodu & Lague, 2012) is only recently becoming more popular in CH (Moyano et al., 2021), while the RANSAC (RANdom SAmple Consensus) model-fitting method is more widespread and allows portions of points to be assimilated into geometric shapes of primitives, such as planes, cylinders, spheres, cones (Schnabel et al., 2007).
In this work, a multi-approach strategy was chosen, adopting first a minimal Voxel Down-sampling (S. Wang et al., 2022) and then a decimation process based on the reduction of non-critical points the are not useful for the subsequent 3D generation steps in the BIM Authoring process. Finally, a classification with CANUPO and a segmentation method with RANSAC were used to extract a specific class of elements from the entire point cloud.

Fig. 1 Gioia del Colle, Italy. Palazzo Nico.

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METHODOLOGY

The application of the Scan-to-BIM approach is oriented to the integration of a point cloud (LiDAR or photogrammetric) into BIM operational flows, during design, checking and management phases. Point clouds need to be optimised and prepared to meet the geometric requirements (LOD and accuracy), for its scheduled applications (such as 3D shape generation or geometric deviation verification and validation), and to be sufficiently manageable in terms of size, or through cloud-based AcDAT systems, and eventually divided up between Teams.
The scene chosen for this study includes clearly identifiable geometries that are challenging to classify manually due to their spatial layout (Fig. 1).
Thus, in order to set up the complete point cloud for BIM procedures and enable a customised management of one architectural feature in particular – the stairs – an operational flow based on decimation and classification phases was proposed (Fig. 2).

Resolution	*1/5*
NOHD	*10.60 / 3.30*
Quality	*4x*
Points Resolution	*28.2 MPts*
Scansion Dimension	*8248 x 3414 Pts*
Color	*RGB + Scalar*

Tab. 1 Laser scanner technical specification.

DECIMATION PROCESS

The strategy used a multi-approach strategy, starting with a basic Voxel Down-sampling and moving on to a decimation process based on removing non-critical points that are not useful for the subsequent 3D generating phases.
We choose to concentrate this application on the vertical connection system consisting of five straight ramps per floor to make the parametric analysis of the different algorithm properties straightforward.
The point cloud was recorded by a TLS survey with the FARO FOCUS 3D 120 instrument, and consists of 84M points by 21 scans, with the following specification (Tab. 1):
The LiDAR survey product creates a point cloud with non-constant density (Fig. 3), which results in fluctuating linear resolution in different sections of the cloud, due to the instrument's irregular positioning in the space and its variable orientation in relation to the building elements.

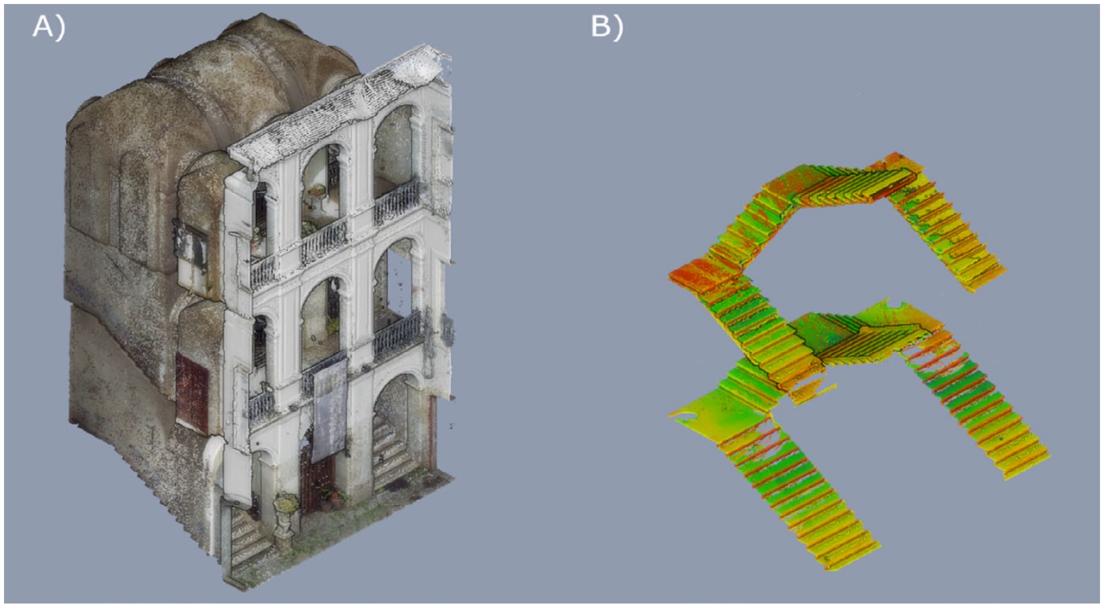

Fig. 2 A) Clipped point cloud; B) Staircase ramp segmentation.

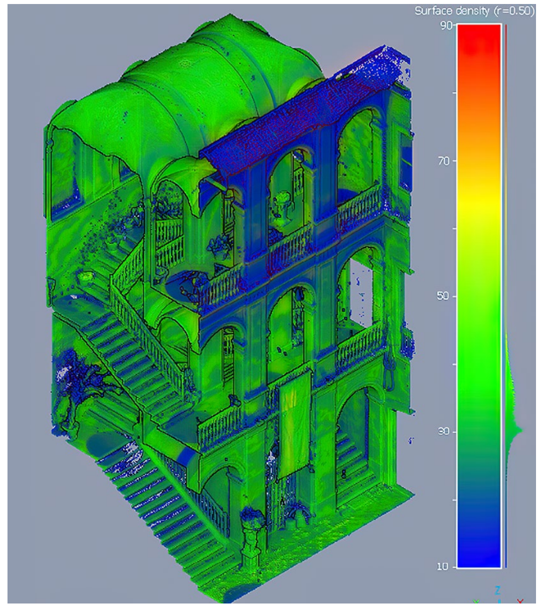

Fig. 3 Point cloud surface density [Mpts/m³].

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For this reason, an initial normalisation process was chosen, so as to equalize the geometric resolution of the points, based on the accuracy and LOD required by the Scan-to-BIM process, using a voxel-based spatial decimation method. Despite being one of the algorithms with the lowest computational load, this simplification method, if configured incorrectly, can result in an oversimplified point cloud with a loss of detail due to the uncritical elimination of points, including even those that may be useful for maintaining formal recognisability.
The approach is based on creating a three-dimensional voxel grid (Fig. 4) in which the distance of each point from the centroid point of the individual voxel is calculated. The point closest to the center is preserved, while the other points are discarded.
The size of the voxel grid impacts the decimation intensity of the algorithm and thus the preservation of the detected details. In this case, to assess the voxel size, a virtual voxelization of the ramp was performed, making a qualitative analysis of the representability and identifiability of the required details (Fig. 5).
The graphical representation of the geometric voxelization of the stair steps facilitates the choice of the minimum resolution required to preserve the morphological features. Furthermore, if the required LOD or geometric precision is known, an analytical evaluation can also be made with respect to the voxel size.
This initial decimation can also be generalised over the entire model, although representability conditions often depend on the area and on the elements.
For the second decimation step, it is important to identify the characterising points, i.e., the points that represent the areas of the point cloud essential for the subsequent 3D generation steps. Such points are usually represented by the edges of the surveyed geometric elements – in this case referred to the profile of the ramp steps.
To identify these points, we based on mean curvature analysis (X. Yang et al., 2015): this process is based on calculating the radius of the segmentation range which identifies the circular selection area determined by comparing the mean curvature value of the chosen point to the average mean curvature of the entire cloud.
The range is narrow in the areas with greater curvatures, whereas it is wide in the areas with fewer curvatures.
However, this iterative procedure implies a significant computational effort, which might delay processing steps

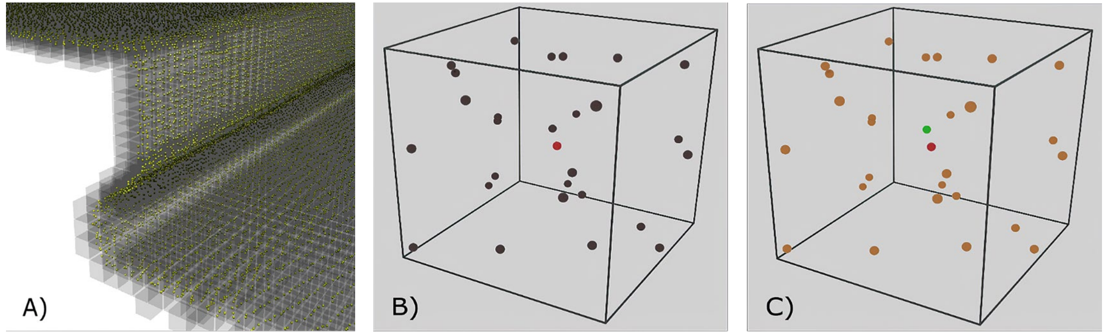

Fig. 4 A) Detail of the voxel grid; B) the red point is the centroid; C) the green one is the nearest point.

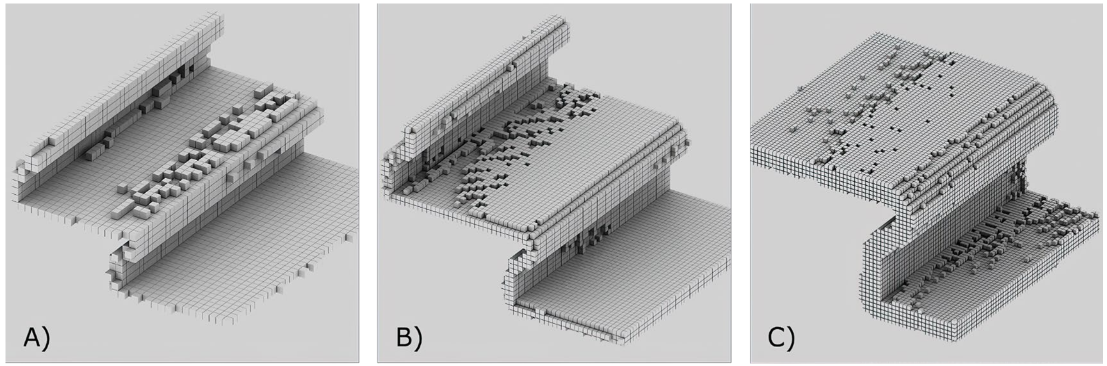

Fig. 5 Voxel size: A) 2 cm; B) 1 cm; C) 0.5 cm.

even though it enables accurate and timely geometric analysis of specific point cloud regions[1].
For this reason, a simplified computation was chosen in this work: for each point, only the mean curvature (Har'el, 1995) was calculated with respect to the neighboring points within a radius of 9 cm – experimentally evaluated with reference to the element sizes to be modeled – which is sufficient to highlight the critical points of non-planar surfaces.
Low mean curvature points, which could potentially indicate non-critical points, were considered as redundant points that are not useful for the 3D model representation.
Applying a filter for points with a mean curvature under a certain value allows a parametric simplification of the planar points, preserving the recognisability of the points – in this case referred to the stairway – useful for three-dimensional reconstruction in the BIM Authoring environment (Fig. 6).
Indeed, in this simplyfing stage, it is crucial to trace the geometries back to their three-dimensional genesis, considering the modelling methods that will be used for the 3D modelling.
For istance, in the IFC4.1 and IFC4.3 schemes, the ramp is defined through the setting of specific classes and entities (Fig. 7).
The dimensions of the vertical connection, the quantity of risers and treads, and finally the profiles that compose the step covering are the parameters for the geometric definition of a ramp in this diagram. The previously filtered points can be used to infer all of this information.
The decimation result must be validated in order to be

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accepted for further processing; hence this verification step is crucial.

CLASSIFICATION AND SEGMENTATION PROCESSES

The purpose of classification techniques is to "label" groups of points that share similar traits. These algorithms are very helpful for categorising architectural elements in the Scan-to-BIM framework in terms of various LODs, allowing them to be retrieved and managed individually by multidisciplinary teams, and allowing them to work concurrently on BIM Authoring procedures.
One of the highlights of these approaches is their design complexity and the challenge of generalising the training process without a baseline dataset, which is necessary to get a good outcome. For this reason, we decided to investigate the use of a straightforward binary spatial classifier called CANUPO (Brodu & Lague, 2012) within an optimisation process aimed to extrapolate the points that make up the staircase ramp profiles.
It was decided to extrapolate a single section of the ramp and use it in the training phase of the algorithm since the spatial shape of the ramps appears to be symmetrical and modular (Fig. 8).
The test revealed some limitations of the algorithm, classifying flights of stairs in an inclusive manner and simultaneously grouping points outside this category, as can be seen from the distribution graph of the point classes during training. The computational simplification used in the calculation phase and a fast but too elementary training approach constitute a restrinction of the algorithm. Another optimisation application can be used to try to improve the segmentation of the staircase ramp points if sufficiently satisfactory results are not produced.
In a subsequent stage, the data resulting from segmentation were handled by locating the points belonging on the inclined planes (Fig. 9) that denote the stair ramps using the RANSAC algorithm (Schnabel et al., 2007), a tried-and-true technique that involves fitting sets of points to simple primitive shapes, suc as planes, spheres, cones, cylinders (Fischler & Bolles, 1981; Oh et al., 2021; Tarsha-Kurdi et al., 2008).
A minimal number of points necessary to define the model, in this istance three non-collinear points, is randomly chosen by the algorithm when identifying a plane in which to insert a group of points.
It calculates the model using the chosen points, e.g., with the least squares approach, and determines how many points in the point cloud fit this model. Then, it identifies points as either "inliers" or "outliers" depending on whether they fall inside a certain distance threshold. The steps are repeated for a fixed number of iterations or until enough inliers has been reached.
This method allowed individual staircase ramps to be isolated from the overall environment, making it simpler to use them in BIM procedures and workflows (Fig. 10).
The segmentation procedure can also be used as a preliminary step on the point cloud to extract only the geometric elements that will be the subject of optimisation. After calculating the average distance between each point and its neighbours, the so-called "orphan points" that are farther away from the average distance plus a number of times the standard deviation are removed.
To make it compatible with the Autodesk Revit® BIM Authoring software, the resulting point cloud, which represents the collection of staircase ramps, was exported in .PTS format and moved within the proprietary Autodesk Recap® processing environment.

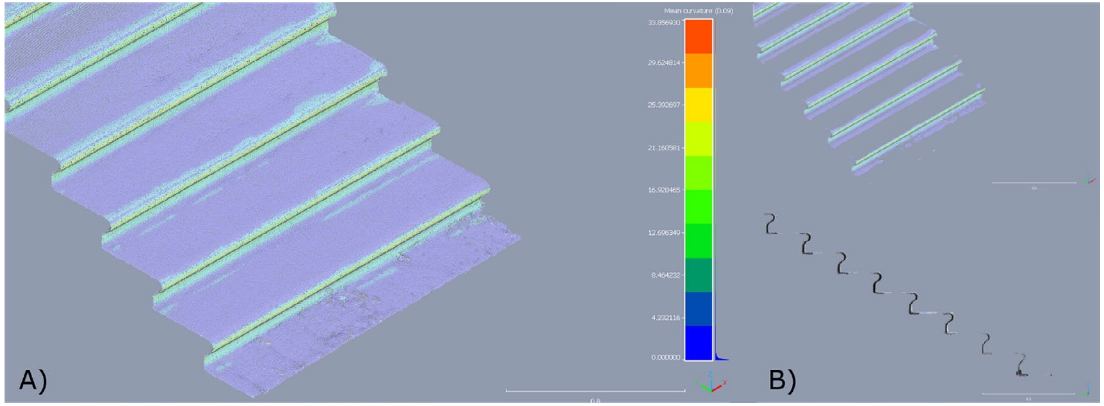

Fig. 6 A) Point cloud of the staircase ramp with mean curvature calculation; B) Filtered point cloud with mean curvature > 2 (total points: 229,786).

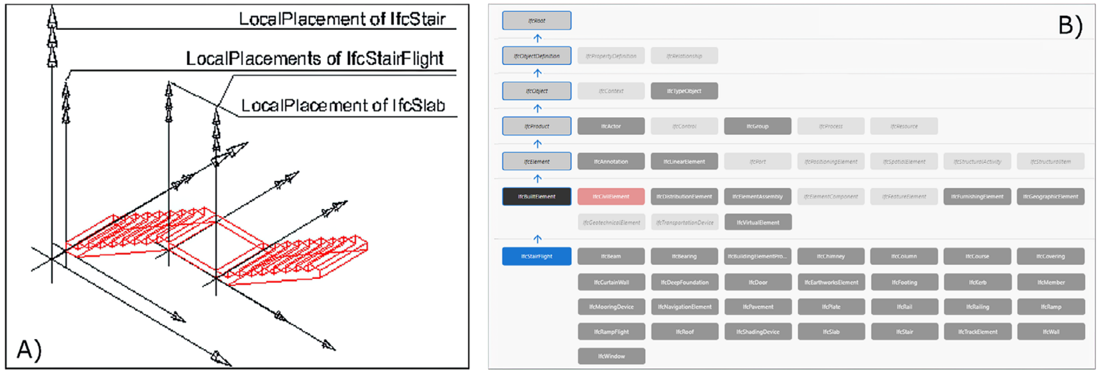

Fig. 7 A) IfcStair type from the IFC 4.1 scheme; B) IfcStair entity inheritance from the IFC 4.3 scheme.

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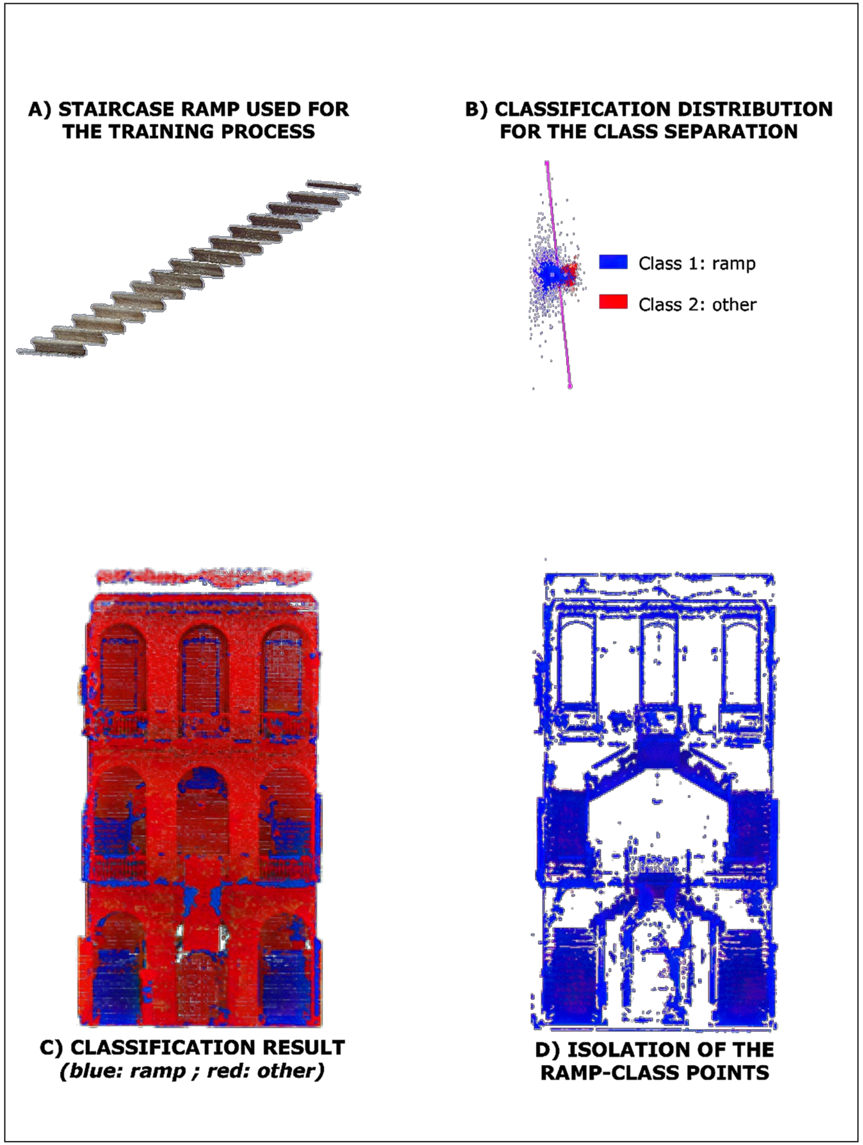

Fig. 8 Training process and binary classification with the CANUPO algorithm.

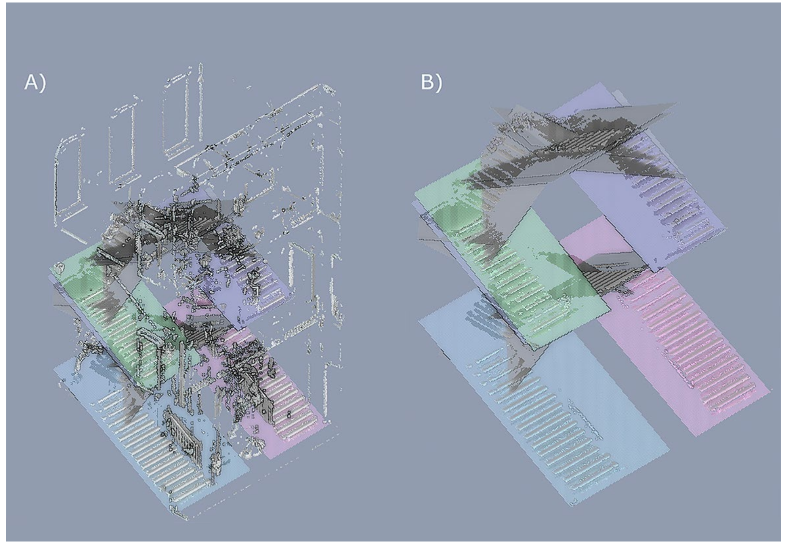

Fig. 9 A) #Class 1 point plans identified by RANSAC 1; B) Isolated #class 1 points

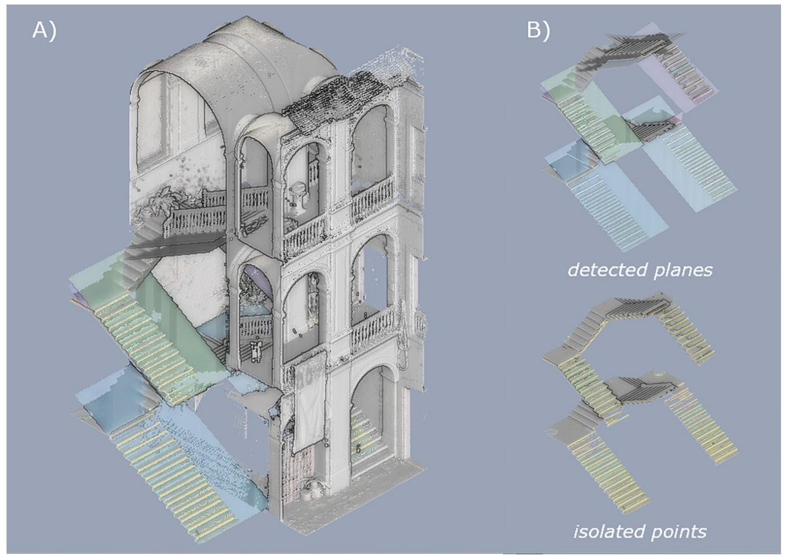

Fig. 10 A) Planes detected by RANSAC shown in the box section of the point cloud; B) Detected planes and isolated points.

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BIM AUTHORING

The ramp block modelling process was put into practise within the BIM Authoring environment with the goal of evaluating the workflow's efficacy (Fig. 11). This included verifying the final product of such processing's geometric accuracy and completeness.
It was possible to separate the staircase body's most distinguishing features by automating the aforementioned method, which supported the subsequent processes (Fig. 12). This method, especially during the training phases, improves a multidisciplinary approach, allowing the designer to identify the points that characterise the elements to be partitioned.

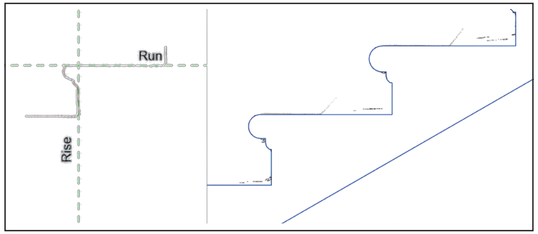

Fig. 11 Using the point cloud processed in the BIM Authoring software.

CONCLUSIONS

This study proved the effectiveness of an automated approach for improving a LiDAR survey for BIM Authoring operations using a free software classification algorithm made available under the LGPL (implemented in CloudCompare) and linked into an operational workflow. The output was refined and enhanced in accordance with the necessary information and geometric requirements. The design of a modular operational workflow allows the optimisation processes to be executed based on the needs required by the case study, even applying them in a different order (Fig. 13). When element categories include different LODs, for instance, it is possible to start with the segmentation phase and then move on to the decimation phase while utilising various simplification settings.

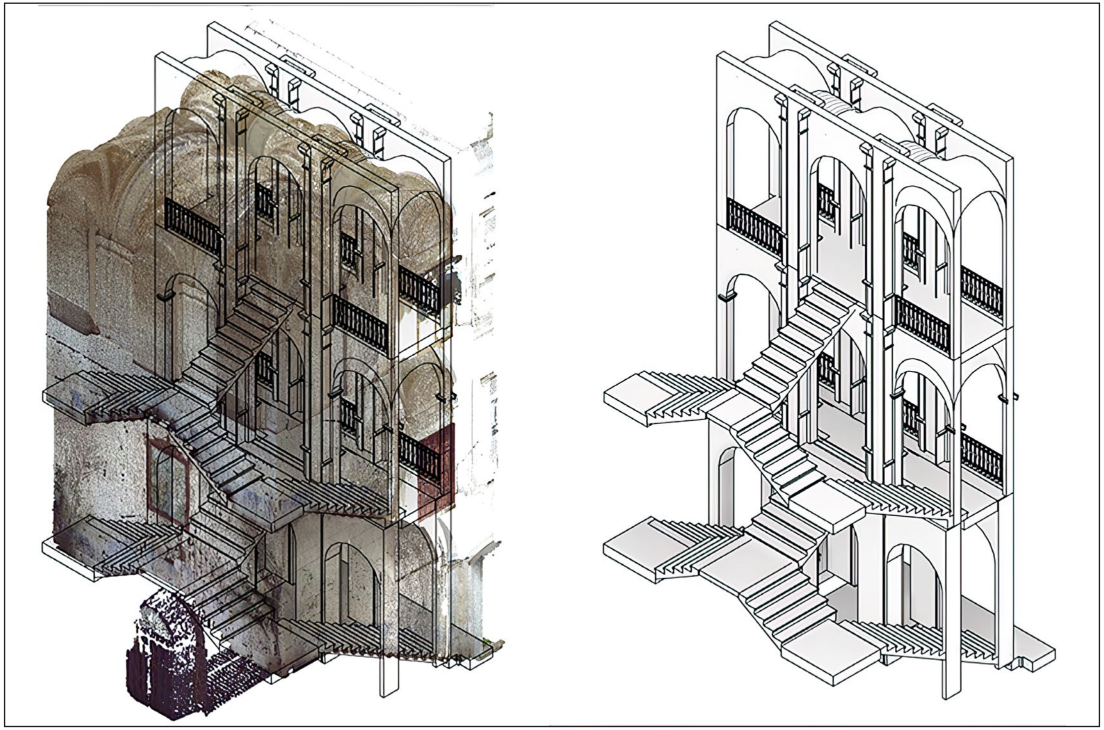
Fig. 12 Portion of the architectural BIM Authoring in the Scan-to-BIM process.

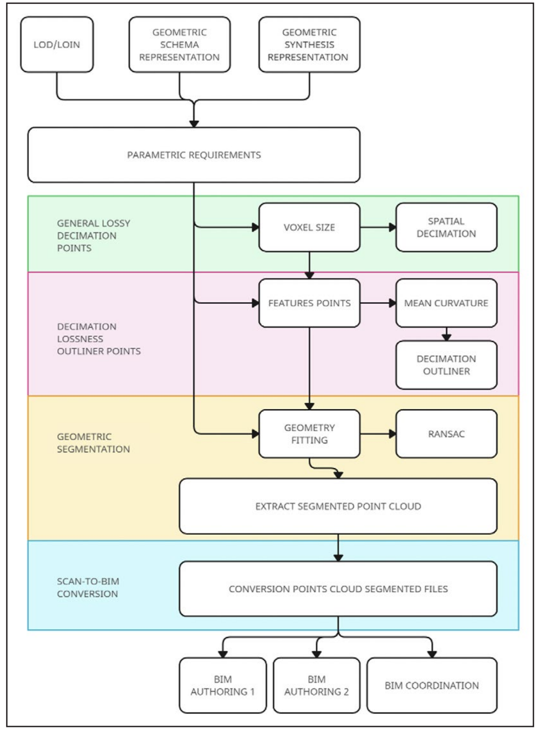

Fig. 13 Workflow optimisation for the Scan-to-BIM process.

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NOTE

[1] $r_i = \alpha \cdot \frac{\overline{H}}{|H_i|}$ where: r_i= radius of the segmentation range;
α = scale factor of the segmentation range;
H = average mean curvature of the entire point cloud;
$|H_i|$ = mean curvature of the single i point.

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