POINT CLOUD CLASSIFICATION OF AN URBAN ENVIRONMENT USING A SEMI-AUTOMATIC APPROACH

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ABSTRACT:

In this contribution a point cloud classification in an urban context has been presented. The aim of the work is to test a semi-automatic classification approach and to verify its usefulness in the scan-to BIM process, and to validate how much it is straightforward for the definition of different point cloud LODs. The work methodology is structured in three phases. The first concerns data acquisition and processing through geomatic instruments and methodologies that guarantee a complete and expeditious survey such as ground-based MMS and UAV for aerial photogrammetry. The second phase concerns the testing of an online software that performs point cloud classifications through AI algorithms. The system allows either to use standard classifiers that are already available, or to create a customizable catalogue of the different classes that one wants to attribute to the urban scene. Following the automatic classification process, where all objects have been identified, manual corrections can be made to improve the classification of objects into specific classes. The third step is object detection and extraction. Here, the relationship between automatic classification, point cloud density, object identification and the various degrees of LOD definition was explored. The higher the LOD, the greater the number of objects that can be identified, particularly those elements related to street furniture and urban facilities. Once these objects have been classified, it is then possible to extract them in interoperable format. This allows such data to be managed and shared through BIM platform.

1. INTRODUCTION

Mobile mapping systems (MMS) have been developed in recent years, which makes it possible to capture 3D point clouds fastly and with a good precision (Di Stefano et al., 2020; Di Stefano et al., 2021a; Di Stefano et al., 2021b). Taking into account the benefits for the utilization of MMS system to collect 3D point clouds of different types of environments, including the urban one, a significant progress has been made in the automatic recognition of 3D object in point clouds in recent years (Xue et al., 2021; Li et al., 2022). In the scan to BIM workflow, one of the main bottlenecks consists of the transformation, with the proper Level of Detail (LOD), of unstructured data, in semantically enriched parametric objects (Badenko et al, 2019; Justo et al., 2021).

In this project, the main goal is to provide a point cloud classification to extract the 3D urban environment objects at different LOD. It might permit flexible usage in different domains, such as Architecture, Engineering, and Construction (AEC), Building Information Modelling (BIM), City Information Modelling (CIM), CityGML (Smart City, 3D-CityModel) and Facility Management (FM) (Naticchia et al., 2020; Binni et al., 2023).

The main contributions of this work are as follows:

- execution of a complete and expeditious geomatic survey through the use of MMS integrated with other survey technologies to obtain a 3D representation of the urban context;
- point cloud classification process through a semi-automatic approach based on AI algorithms;
- verification of the semi-automatic classification approach based on object identification and its usefulness for a scan-to-BIM process;
- validation of how much it is straightforward for the definition of different point cloud LODs.

The paper is structured as follow. Section 2 is devoted to a brief analysis of classification techniques present in the literature. The methodology of work is described in Section 3. Section 4 discusses the methodology performed. Finally, the conclusions are outlined in Section 5.

2. STATE-OF-THE-ART

Several approaches have been shown in the literature to perform a classification of objects describing an urban context from the point cloud. These are large point clouds with a certain point density, which are complex to manage. In particular, there are few examples in the literature that associate point cloud classification procedures in an urban context with the identification of different LODs, based on the characteristics of the point cloud itself (Verdie et al, 2015; Gorgoglione et al., 2023). Thanks to the development and application of machine learning (ML) and deepl learning (DL) algortims, Artificial Intelligence (AI) has become a very helpful tool for performing point cloud classifications and LODs definition.

First of all an explication, we talk about classification and not segmentation. They seem similar concepts but while segmentation provides groups of points having similar characteristics, classification assigns points to specific classes, applying different criteria (Grilli et al., 2017; Pierdicca et al., 2019; Matrone et al., 2022).

One method for an automatic classification is based on geometrical and topological parameters to identify objects, separating the point cloud into different blocks (Balado et al., 2018). Cura et al. (2016) proposed an automatic classification using geometrical ordering based on the closest point to octree cell center. Other parameters can be the local height variance of the object and the height of the corresponding trajectory points (Li et al.,

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2022). Another methodology for the automatic and unsupervised classification is based on the voxel parameter of the point cloud which allows to identify the objects using the number and the spatial location of the points (Poux and Billen, 2019). Often these techniques can't guarantee expected results: the LOD of smaller objects,elements of street furniture, that are not always achieved. In other cases, the creation of a training dataset has led to the adoption of a supervised classification through ML-DL algorithms. Examples in literature can be found in the work carried out by Zou at al. (2021) where, by means of the use of ground truth, they defined some classes of urban objects. However, they didn't reach the LOD for smaller objects, falling within the category of urban furniture.
Based on these and other previous research activities, the aim of this work has been to investigate the relationship that exists between automatic classification processes and the definition of LODs, and in which cases it is necessary to correct the results for a better interpretation of the objects in the urban scene.

3. METHODOLOGY

This section concerns the methodological approach adopted. After carrying out the geomatic survey of the urban area, we proceed with the data processing, to obtain the point cloud survey. This is followed by the part dedicated to the semi-automatic classification of the point cloud by AI algorithms. Once the classification is completed, the extraction of the recognised objects can proceed, according to the LODs (Figure 1).

3.1 Case study

The project concerns the digital reconstruction of the RAI Saxa Rubra headquarters in Rome. A built environment context consisting of several buildings characterized by the presence of various components of street furniture has been chosen as an application test. The case study concerns an urbanized area of approximately 125 mq consisting of buildings, roads, vegetation and a large car park (Figure 2). The buildings are prefabricated constructions with an elevation of 3-4 storeys. The urban context has some of the main characteristics of a built environment where, in addition to buildings and roads, there are elements of street furniture, e.g. curbs, public lighting poles, litter bins and components of the urban technical infrastructure such as manholes, fire and video surveillance systems.
Within the whole project, the implementation of modelling procedures according to the BIM standard for the management of information modelling for facility management purposes is foreseen.

Figure 2. Map of the surveyed urban area (from Google Earth)

3.2 3D survey

Geomatics devices with a fast and agile data acquisition solution were used to perform a complete, fast survey of the case study area. These solutions are represented by a Mobile Mapping System (MMS) device composed by a 3D LiDAR sensor with integrated camera and an Unmanned Aerial Vehicle (UAV) equipped with digital aerial photogrammetric camera.

a. b.

Figure 3. Devices used for 3D survey: a. GeoSLAM Zeb Horizon as MMS; b. Parrot Anafi as UAV.

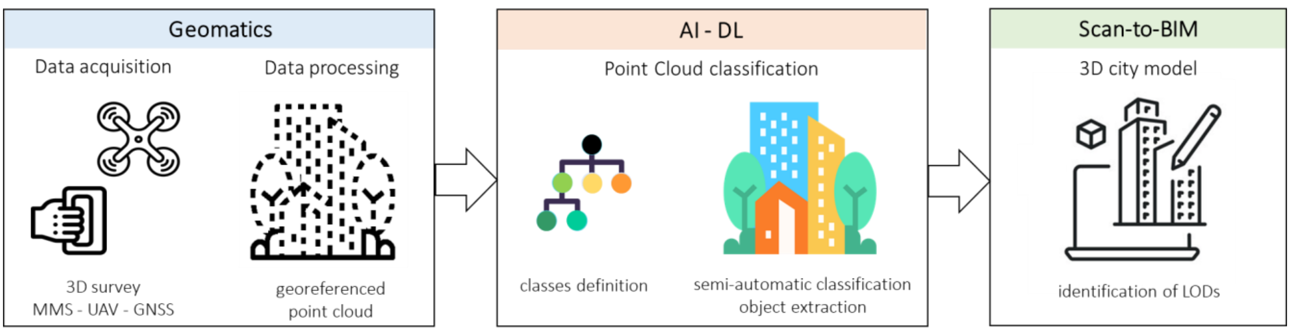

Figure 1. Methodology workflow

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GeoSLAM Zeb Horizon (Figure 3a) was used for the MMS survey system, equipped with SLAM (Simultaneously Localization and Mapping) technology. GeoSLAM Zeb Horizon (Table 1) is a commercial and hand-held mobile scanner, mounting VPL-16 LiDAR system and MEMS IMU. As an accessory, the ZEB Cam is a color camera for GeoSLAM ZEB Horizon, embedding a Hawkeye Fire-246 fly 8SE action video camera. The images collected by the camera can be viewed alongside the 3D point cloud provided by the ZEB Horizon and used to extract contextual information. The data collection by means of Zeb Horizon is highly automated. The raw laser data is co-registered in a 3D point cloud, through the internal SLAM algorithm.

Table 1. Technical specifications of GeoSLAM Zeb Horizon

Mobile device	
Weight	100 g
Size	108x216x226
Range	100 m
Laser	Class 1 / λ 903 nm
FOV	360° x 270°
No. of sensors	16
Battery life	appox. 3 hours
LiDAR data	
Scan rate	300,000 points/s
Scan range noise	± 30 mm
Colourised point cloud	yes
Intensity	yes
Relative accuracy	up to 6 mm
Raw data file size	100-200 MB/minute
Processing	Post
Additional accessory	Data logger

An aerial photogrammetric survey was also made with Parrot Anafi (Figure 2b), a UAV device to integrate the data achieved on the ground. The UAV device was flown at a height of 30 m above the ground (GSD ~ 1,02 cm). Table 2 shows the main technical characteristics of the UAV device and the imaging system.

Table 2. Technical specifications of Parrot Anafi

Drone	
Weight	320 g
Size unfolded	175x240x65 mm
Max flight time	25 min
Max horizontal speed	15 m/s (55 km/h)
Max transmission range	4 km with controller
Controller	PARROT Skycontroller 3
Imaging system	
Focal lenght	23-69mm
Aperture	f/2.4
Photo resolution	21 MP (5344x4016)

The data acquisition campaign took place over two days. Ten closed-loop footpaths, around buildings and along the roads, with MMS device, were made and moreover to allow an overlap to facilitate the merging of the point clouds of the entire surveyed environment, they were intersected one each other. The UAV survey was carried out in manual mode for the presence of electromagnetic sources (for example a transmission tower) that it makes impossible to exploit a preset flight plan in automatic mode. Table 3 summarizes the data acquired with both sensors mentioned above.
In order to obtain geographic coordinates and to easily align and merge the acquired point clouds, a survey was carried out with a GNSS receiver to identify the position of the targets distributed in the case study area. Targets with dimensions of 50x50 cm were used, some as GCPs and others as check points.

Table 3. Data acquired by MMS and UAV

Building	MMS [pts.]	UAV
A	109,611,948	2521 photos
B	55,192,832	
C	67,392,459	
D	115,453,721	
E	66,027,681	
F	36,485,273	
G1	142,754,838	
G2	113,184,452	
H1+H2	45,118,906	
I	52,248,241	
Total [pts.]	803,470,351	239,801,439
Space memory	82 GB	33 GB

The subsequent data processing phase took five working days in the laboratory. The data processing involved the recording, elaboration and creation of the point clouds using the following software: GeoSLAM Hub for LiDAR data and Pix4D for photogrammetric survey (Table 4).
To solve this task, since the files to be processed are heavy and sufficient memory space is needed to save the data, a hardware with i9-10940X - Intel Core™ processor was used.

Table 4. Data processing phase

Data acquisition technique	Data processing time	Data exporting time
MMS (no. 10 point clouds)	almost 2,5 hours	almost 1 hour
UAV photogrammetry	almost 9,5 hours (densification and textured mesh generation)	15 min

The .las format files were exported in order to proceed with alignment, merging and combination of the point clouds, in CloudCompare software, through georeferencing with the coordinates acquired by the GNSS receivers (Table 5).

Table 5. Georeferencing operation

Processed data	Alignment	RMSE [m]
MMS point cloud	MMS - GNSS	~0,018
UAV point cloud	UAV - GNSS	~0,021

3.3 Point cloud classification

After the 3D urban content representation, a point cloud classification was performed to identify the components of the urban environment. For this purpose, an online software as Poinlty (Pointly, 2022) was tested for a semi-automatic classification approach. Pointly is an intelligent, cloud-based software solution, to manage and classify big data in 3D point clouds. The innovative AI techniques enable an automatic as well as accelerated manual classification of data points within point clouds, making it faster and more precise. Our benchmark aims for analyzing the quality of 3D object detection operations to verify LOD, achieved by such software.
To start a project on Pointly, first it has to define the classes using the classifiers suggested by the standard catalogue. There is also the possibility of customizing the classifiers by removing or adding classes relating to the case study. The standard classifier contains the following classes: ground-road, vegetation, building, poles, cars.

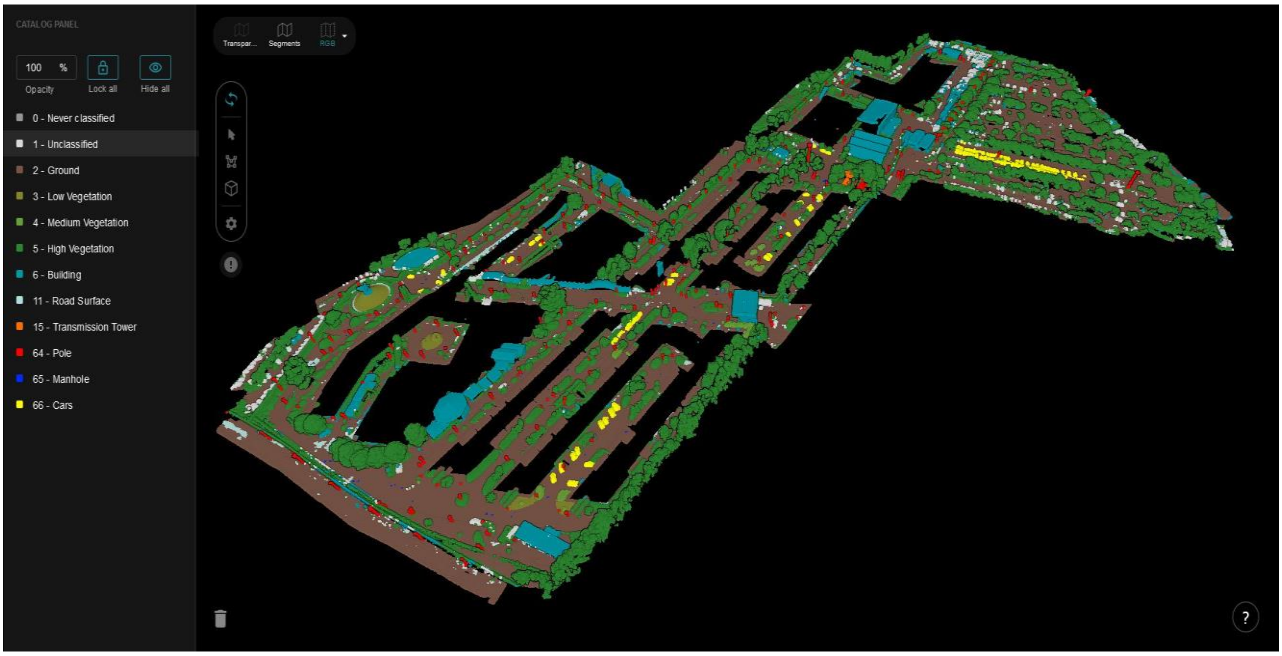


Figure 3. Test no.1: 3D point cloud classification by semi-automatic approach

Then it proceed with the uploading of the point cloud (.las format), which will undergo the automatic classification process. The software is able to group points automatically into predefined classes, by means of deep learning (DL) algorithms, on the basis of geometric and spatial features or/and RGB data of the points, as works an unsupervised classification. The feature parameters for object detection are intensity, elevation, total number of returns for a given pulse and GPS time.
Points didn't classify were grouped under the class called "unclassified".
If during the DL classification process some attributes of the points are not identified and don't match with any class, finally they are grouped in the class "never classified".
The online software also allows you to create a catalogue of classes after which you can edit, remove, or add classes as you want. In the specific case of this project, specific classes were created to enrich object recognition. For example, some classes were added for ground and road referring to the elements that make up the road surface, e.g. manholes, pavements-curbs, parking spaces. For the vegetation macro-class, three classes were created: low, medium, and high vegetation. For buildings, a class was created for external staircase structures and another for building openings. For the standard class of poles, it was decided to divide the elements into signals, light poles and fire-fighting system elements such as fire hydrants. To complete the classification of objects in the urban context, some classes were included for litter bins and video surveillance systems.
The usefulness of the object class called "unclassified", generated after a starting step of automatic classification, shows how the system is able to identify objects that might falling into one of the classes modified or added in the customized catalogue.
If you decide to use custom classifiers, the point cloud submitted for classification is first processed with an standard automatic classification process and then a manual correction can be made to adjust the classification by assigning the classified points to additional classes. The selection of these points, for the intuitive use of the DL software, can be done manually selecting the following tools: segment selector, polygon lasso tool, 3D bounding box. The selection tools provide smooth and precise object classification.

3.3.1 Test no. 1

Figure 3 shows a first semi-automatic classification that has been tested over the entire case study area. To simplify the process and make the classified elements more visible, the main higher buildings have been removed.
The example shows an approach based on a custom classifier where in addition to the standard ground-road, vegetation, building, poles and cars classes, the transmission tower and manholes classes have been created. For the last two classes, manual correction of the already processed automatic classification was used.

3.3.2 Test no. 2

To go into detail on the quality of object classification, a small portion of the urban area was subjected to a second test. A custom classifier containing all the classes concerning the case study has been created. Table 5 contains all the classes that have been entered into the customized classifier used as a test. Figure 4 show the outputs that are obtained following the three classification modes referred to in Table 5.
The respective classes of the urban context are identified on the basis of the classification method. Many classes were automatically recognized by the system and thanks to the simple manual correction it was possible to attribute points to the specific classes created.
For a smaller number of classes, it was necessary to resort to a completely manual classification. These are elements that have geometric and spatial similar characteristics to other classes, such as road surfaces and pavements, or elements part of deliberately added classes, such as car parks. These, for different reflectance value, sometimes identifying the horizontal marking lines, or the intensity scale, can be easily recognized for manual selection. Other objects, although identified, are very small elements that require a manual approach, such as video surveillance system cameras.
In relation to the class "building openings" there is a remark to do. In the case of prefabricated buildings, the building openings appeared as continuous glass windows, don't detect by the LiDAR sensor, due to the reflectivity of the material, which the laser beam affects.

Table 5. Point cloud customized classification (Test no. 2)

Mode	Automatic classification	Automatic classification with manual correction	Fully manual classification
Classes	Ground - Road	Road surface	Parking spaces
			Pavement - Curbs
		Manholes	
	Vegetation	Low vegetation	
		Medium Vegetation	
		High Vegetation	
	Building	Staircases (external)	
			Building openings
	Poles	Signals	
		Light poles	
		Fire hydrants	
	Cars		
	Unclassified	Bins	
			Video survillance cameras

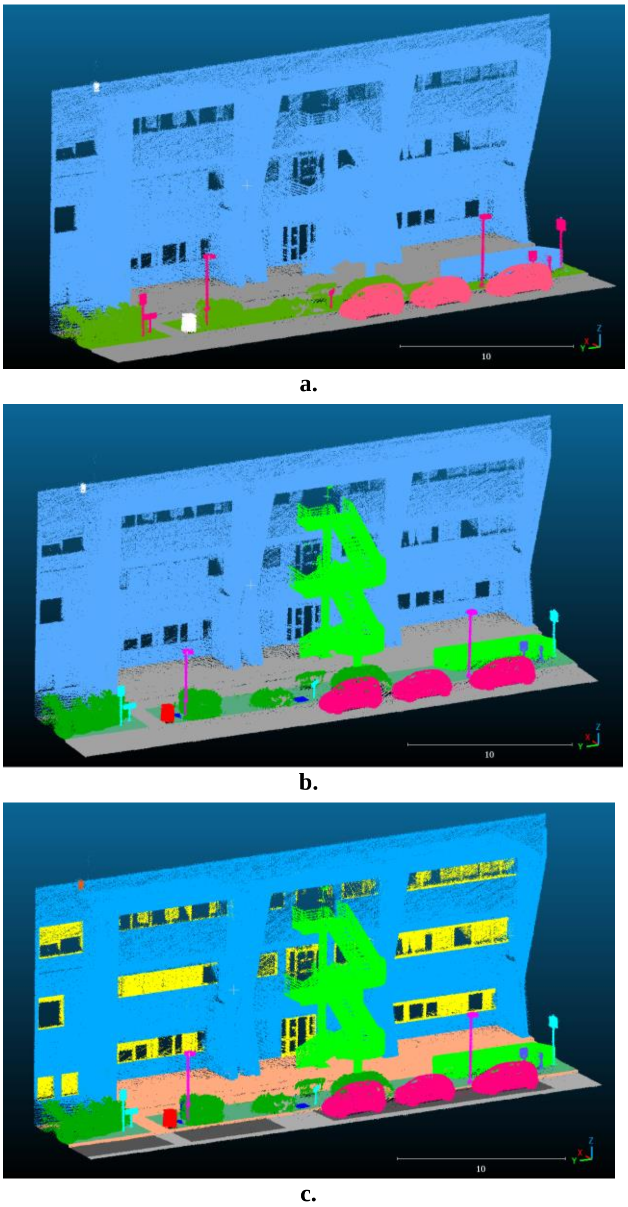


Figure 4. Test no. 2. Classification output: **a.** automatic; **b.** automatic with manual corrections; **c.** addition of fully manual classes

Table 6 summarizes all data relating to this second semi-automatic classification test.

Table 6. Classification stats of Test no. 2

No. points	5.829.709
Space memory	148 MB
Time to upload point cloud	2 minutes
Automatic classification process	15 minutes
Manual correction and classification	almost 1 hour
Export of classified point cloud in .las format	5 minutes

3.4 Object detection and extraction

Once the classified point cloud has been exported, any point cloud management software can be used to work with the various classes. Classified objects also have as scalar field the class indexes a result of the online semi-automatic classification processing. Classified objects can be managed either as a whole class or individually. This will then allow the various objects to be assigned an identification code. Thanks to the georeferencing of point clouds during data processing, classified objects are also provided with geospatial data, useful to determine the correct position on the map of the analysed case study area.

Pointly also allows point cloud classified objects to be converted into other formats, e.g., into CAD format for technical drawing software or into shapefile or GeoTIFF, GeoJSON format for GIS.

Referring to the final use of these classified objects that are to be included in a management platform for building structures as BIM, urban areas as CIM, and construction sites as Facility Management, a deepening between automatic classification and LOD became useful. For the identification of LODs, reference is made to the Open Geospatial Consortium (OGC) standards. This analysis is based on the interpretation of the data on the basis of the decreasing resolution, e.g., quantity of points, of the point cloud.

Based on a portion of point cloud of Test no. 2 previously described, Table 7 shows this relationship between the automatic classification, the recognition of the objects and the relative LOD. For a better understanding, this analysis refers only to the automatic approach operated by the online software. Those objects which are not identified among the standard classes, but which can be attributed to other classes with the manual correction and selection, are taken into consideration. In this context, the objects that must be classified through fully manual operations by the operator are omitted.

The original point cloud, in its total number of points, corresponds to the highest LOD by convention: LOD 4. In this case all standard classes, ground-road, building, vegetation, poles and cars are correctly identified with the automatic approach. In this classification process there are also elements that are identified but not associated with any class. Through manual correction, these can be attributed to specific classes included in the catalog of custom classifiers, referred to in Table 5.

As a matter of practicability, management, and use of the often-heavy point cloud, one can resort to reducing the number of points through filtering and resampling operations. In our case a random mode was chosen to resample.

Regarding the filtering operations, this was based on the data properties of position, time and semantic attributes, maintaining the same characteristics as the original data.

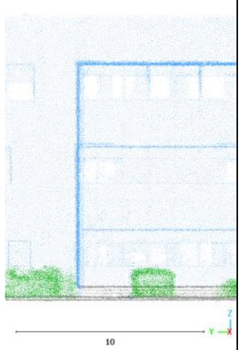
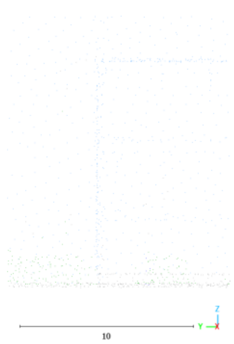
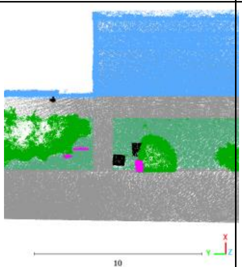
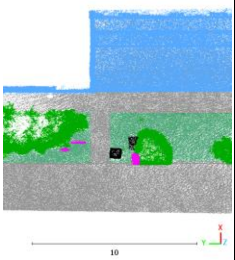
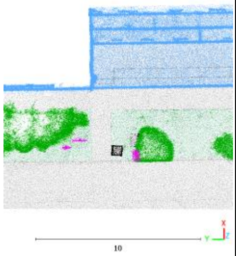
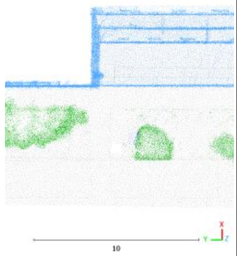
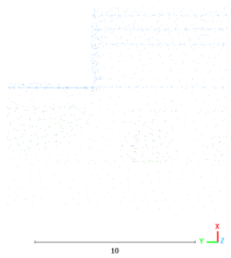
After 75% resampling and initial filtering of the original point cloud, referring to Test no. 2, this point cloud was subjected to automatic classification to test again the online software for the

object recognition. Standard classes were easily recognized. There are objects that are identified but not classified in the standard classes because of they have different geometric and spatial characteristics to the standard classes, according to the deep learning algorithms. These unclassified objects are fewer in LOD 4, and this is related to their dimensional and spatial characteristics. Based on the final quality of the point cloud and on the recognition of the architectural and some urban elements, the resampling stops at LOD 3.
We continue with a new automatic classification of the sub-sampled original point cloud at LOD 2. The buildings are recognized by roofing elements and the vertical surfaces by the height. The vegetation objects are still identified. Street furniture elements are less represented in the form of points. Medium-large sized objects such as poles, bins and cars are identified.
Proceeding with the down-sampling process to the total value of the points equal to 25% of the original data, a relatively light point cloud is obtained. Uploaded to the online software it is processed and tested for automatic classification. The result had the following result: the standard classes of ground-road, building and vegetation were largely identified, but the manual correction intervention was necessary to make the correct modifications of the belonging of the points to the three classes. In this case, detail quality of LOD 1 can be guaranteed. By reducing the number of points corresponding to a very low percentage of original data to a minimum, all information relating to the characteristics of the respective points is lost. In this case it is not possible to proceed with an automatic classification as the system is not able to recognize any object. Analyzing the point cloud obtained, it is possible to visually recognize the edges of the basic components of the urban context, e.g., buildings and ground surface. We therefore have a coarser level corresponding to LOD 0 from which it is possible to obtain a digital model of the terrain in two and a half dimensions, on which an urban map may be draped.

4. DISCUSSION

The issue that has been addressed concerned the evaluation of this point cloud classification method by analyzing the semi-automatic classification effectiveness of the software tested. This methodology is evaluated on the basis of the correct interpretation and selection of objects, both an automatic and manual approach, and on the speed of processing based on the time frame.
Pointly offers two types of service: free and professional. The free account allows the user to upload a limited number of point clouds with max. 15 million points (300 MB), whereas exports are disabled. The professional account offers access to all functionalities and enables creating an unlimited number of projects.

Table 7. Relationship between automatic classification and LOD based on increasing point cloud down-sampling

Front view					
Top view					
LOD	LOD 4	LOD 3	LOD 2	LOD 1	LOD 0
% Pts.	100%	75%	50%	25%	> 25%
Notes	All standard classes are automatically classified. Manual correction can be used to identify all objects to assign to other classes.	All standard classes are automatically classified. Manual correction can be used to identify less objects to assign to other classes.	Classes of building, ground-road and medium/high vegetation, poles are recognized automatically. Few identified elements can be assigned to other classes.	Classes of building, ground-road and vegetation are partially recognized automatically with a minor manual correction.	No automatic classification. You are only able to recognize visually the edges of the building and the horizontal surfaces on the ground.

The usefulness of this software lies in the a priori definition of a catalogue of classifiers, which can be standard, e.g., provided by the system itself, or customizable with the possibility of adding or modifying classes by the user according to the case study. The same catalogue can be associated with one or more-point clouds subjected to the same classification. The classes provided by the system already contain DL algorithms for feature-based object recognition such as intensity values of the LiDAR scans, RGB data and geometric and spatial features of the points. For classes that are added or modified, there is no possibility of integrating such algorithms and thus objects will be "unclassified" although they will be identified for their different characteristics compared to standard classes.

For this latter category, Pointly enables an accelerated manual classification of data points within point clouds using innovative AI techniques.

A first weakness consists in the performing the unsupervised classification of the objects, although a manual contribution helps the software to improve the classification procedures. As far as the recognition of smaller objects such as street furniture complements is concerned. Therefore, the semi-automatic method must be resorted to, through the manual detection of these objects. This is partly time-consuming, but for the LOD and the degree of confidence, in the definition of minor classes to be achieved, it is necessary.

A second consideration it is related the possibility to test a neural network on the specific classes for the street furniture, but the problem is that there is no such granular annotation to be able to train the network. The current limitation concerns precisely the training datasets as well as the computational resources. Moreover, the classification does not provide statistic data in relation to the degree of accuracy, calculating metrics that can be analysed and compared. So, exporting the .las file of the classification result, it is possible to further analyze the accuracy with any external point cloud management software.

The purpose of the performed tests was to test the system's ability to carry out automatic classification on the basis of point density and point cloud resolution, associated with various LODs. What emerged was that the automatic classification of the main standard classes (ground-road, building, vegetation) worked up to an order of magnitude of 25% of the point density of the original point cloud.

Through a progressive down-sampling operation and subsequent automatic classification processing, we were able to associate a certain point density value of the point cloud with a specific LOD. This makes it possible to determine how detailed the point cloud must be and also to measure the time the system takes to perform this semi-automatic classification.

In the case in which the objective of the project is to be able to identify all the elements of street furniture and related to urban facilities, a level of detail similar to LOD 4 is required since several elements are of a small order of magnitude. In this case, thanks to the large quantity of points acquired per second by the MMS used, the maximum obtainable density of the point cloud is satisfactory.

For a purely architectural project where the essential elements describing an urban context are taken into consideration, e.g., the road infrastructures, the building components, and the possible presence of vegetation, one can dwell on the classification of the point cloud reduced by half which corresponds to a LOD 2 or at LOD 1.

Given that in this case the buildings were not particularly high, and the MMS operating range was able to reach the edges of the roofs, another factor to be taken into consideration, which influences the density of the point cloud, it is the result on the basis of the distance of action of the laser beam from the scanner. If you operate at ground level, the points describing the parts of surfaces located at a certain elevation will be less dense and this also influences the classification results. It is true that the point cloud obtained from aerial photogrammetry can fill the parts that cannot be detected from the ground. However, the low quantity of points is not always satisfactory to compensate for the density of the point cloud in those parts that are at a large operational range from the laser beam of the MMS.

5. CONCLUSION

In this contribution a semi-automatic classification approach in an urban context has been illustrated.

Having identified a case study, the first step concerned the survey using geomatics instruments. To produce a fast and complete survey, an MMS composed by with a LiDAR system with SLAM technology and integrated camera was used in combination with a UAV aerial photogrammetry system. The data obtained from the second survey technique were integrated to the point cloud obtained from the MMS, which was used at ground level, this to guarantee the completeness of the survey. The devices used in this project are GeoSLAM Zeb Horizon as MMS and the Parrot Anafi drone as for aerial photogrammetry. The processed data obtained from the two survey techniques were combined thanks to the insertion of geospatial information through the georeferencing of the targets detected with a GNSS system.

The second step of the project concerned the classification of objects in the urban context through AI techniques. For this project, the choice fell on the testing of Pointly software. Pointly is a cloud-based solution allowing to manage and classify 3D point clouds. The test served to verify not only the speed and timeliness but also the effectiveness of performing the semi-automatic classification. The results of two tests are shown, one that concerns the entire urban context and another that interests in detail a portion of it. In particular, the second test shows in deep the methods of classification of the semi-automatic approach. The software used makes it possible to define a catalog of classifiers where the standard classes already supplied are present, such as those of ground-road, building, vegetation, poles and cars. These classes are automatically recognized thanks to the characteristics of the objects that are identified such as the intensity values of the LiDAR scans, RGB data and geometric and spatial features of the points. There is the possibility of creating a catalog with personalized classifiers where other classes can be added according to the user's choice based on the case study. These additional classes are not automatically recognized by the software when submitting the point cloud to classification processing. Thanks to an intuitive manual classification approach through AI techniques, you can apply manual corrections to associate objects with their respective classes.

The classification result is not validated through the calculation of the metrics, that the software does not provide, therefore we based ourselves on the visual interpretation of the results and on the utility of the software in executing this classification.

However, we proceeded with the analysis of the automatic classification through a progressively decreasing sampling of the number of the point cloud in order to be able to determine the different LODs. Therefore, an attempt was made to determine a relationship between automatic classification and the respective LODs, according to the OGC standards. Table 7 summarizes this type of analysis performed.

The third step concerns the phase of object detection and extraction. The various objects of the urban context are determined according to the purpose of the project and therefore to their necessary LOD. Higher is the LOD, greater is the number of objects that can be identified. For example, in LOD 4 it is possible to recognize even small-sized elements some urban facilities such as inspection, surveillance and fire prevention systems. Other elements concern urban furniture such as vertical signs and litter bins. Once these objects have been classified, it was then possible to extract them in an interoperable format to be able to manage them externally. A solution of this methodology will be able to quickly guarantee the upload, management of this data through BIM or CIM system sharing platforms, particularly for FM or urban emergency situations.

REFERENCES

Badenko, V., Fedotov, A., Zotov, D., Lytkin, S., Volgin, D., Garg, R. D., & Liu, M. (2019). Scan-to-BIM methodology adapted for different application. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, XLII-5/W2, 1–7, https://doi.org/10.5194/isprs-archives-XLII-5-W2-1-2019

Balado, J., Díaz-Vilariño, L., Arias, P., & González-Jorge, H. (2018). Automatic classification of urban ground elements from mobile laser scanning data. *Automation in Construction*, 86, 226-239. https://doi.org/10.1016/j.autcon.2017.09.004

Binni, L., Naticchia, B., Corneli, A., & Prifti, M. (2023). Development of augmented BIM models for built environment management. In *ECPPM 2022-eWork and eBusiness in Architecture, Engineering and Construction 2022* (pp. 469-476). CRC Press. ISBN 9781003354222

Cura, R., Perret, J., & Paparoditis, N. (2016). Implicit LOD using points ordering for processing and visualisation in Point Cloud Servers. https://doi.org/10.48550/arXiv.1602.06920

Di Stefano, F., Cabrelles, M., García-Asenjo, L., Lerma, J. L., Malinverni, E. S., Baselga, S., ... & Pierdicca, R. (2020). Evaluation of long-range mobile mapping system (MMS) and close-range photogrammetry for deformation monitoring. A case study of Cortes de Pallas in Valencia (Spain). *Applied Sciences*, 10(19), 6831. https://doi.org/10.3390/app10196831

Di Stefano, F., Chiappini, S., Gorreja, A., Balestra, M., & Pierdicca, R. (2021). Mobile 3D scan LiDAR: A literature review. *Geomatics, Natural Hazards and Risk*, 12(1), 2387-2429. https://doi.org/10.1080/19475705.2021.1964617

Di Stefano, F., Torresani, A., Farella, E. M., Pierdicca, R., Menna, F., & Remondino, F. (2021b). 3D surveying of underground built heritage: Opportunities and challenges of mobile technologies. *Sustainability*, 13(23), 13289. https://doi.org/10.3390/su132313289

GeoSLAM Zeb Horizon. Available online: https://geoslam.com/solutions/zeb-horizon/ (Accessed on 15 May 2021)

Gorgoglione, L., Malinverni, E. S., Smaniotto Costa, C., Pierdicca, R., & Di Stefano, F. (2023). Exploiting 2D/3D Geomatics Data for the Management, Promotion, and Valorization of Underground Built Heritage. *Smart Cities*, 6(1), 243-262. https://doi.org/10.3390/smartcities6010012

Grilli, E., Menna, F., & Remondino, F. (2017). A review of point clouds segmentation and classification algorithms. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, 42, 339. https://doi.org/10.5194/isprs-archives-XLII-2-W3-339-2017

Justo, A., Soilán, M., Sánchez-Rodríguez, A., & Riveiro, B. (2021). Scan-to-BIM for the infrastructure domain: Generation of IFC-compliant models of road infrastructure assets and semantics using 3D point cloud data. *Automation in Construction*, *127*, 103703. https://doi.org/10.1016/j.autcon.2021.103703

Li, F., Zhou, Z., Xiao, J., Chen, R., Lehtomäki, M., Elberink, S. O., Vosselman, G., Hyyppä, J., Chen, Y. & Kukko, A. (2022). Instance-aware semantic segmentation of road furniture in mobile laser scanning data. *IEEE transactions on intelligent transportation systems*, 23(10), 17516-17529. doi: 10.1109/TITS.2022.3157611.

Matrone, F., Paolanti, M., Felicetti, A., Martini M. and Pierdicca, R. (2022) BubblEX: An Explainable Deep Learning Framework for Point-Cloud Classification. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 15, pp. 6571-6587, 2022, doi: 10.1109/JSTARS.2022.3195200.

Naticchia, B., Corneli, A., & Carbonari, A. (2020). Framework based on building information modeling, mixed reality, and a cloud platform to support information flow in facility management. *Frontiers of Engineering Management*, 7, 131-141. https://doi.org/10.1007/s42524-019-0071-y

OGC - Open Geospatial Consortium. Available online: https://www.ogc.org/standards/ (Accessed on 10 January 2023)

Parrot Anafi. Available online: https://www.ogc.org/standards/ (Accessed on 15 May 2021)

Pierdicca, R., Mameli, M., Malinverni, E. S., Paolanti, M., & Frontoni, E. (2019). Automatic generation of point cloud synthetic dataset for historical building representation. In *Augmented Reality, Virtual Reality, and Computer Graphics: 6th International Conference, AVR 2019, Santa Maria al Bagno, Italy, June 24–27, 2019, Proceedings, Part I 6* (pp. 203-219). Springer International Publishing. DOI: 10.1007/978-3-030-25965-5_16

Pointly. Available online: https://pointly.ai/ (Accessed on 06 June 2022).

Poux, F., & Billen, R. (2019). Voxel-based 3D point cloud semantic segmentation: Unsupervised geometric and relationship featuring vs deep learning methods. *ISPRS International Journal of Geo-Information*, 8(5), 213. https://doi.org/10.3390/ijgi8050213

Verdie, Y., Lafarge, F., & Alliez, P. (2015). LOD generation for urban scenes. ACM Transactions on Graphics, 34(ARTICLE), 30. https://doi.org/10.1145/2732527

Xue, F., Wu, L., & Lu, W. (2021). Semantic enrichment of building and city information models: A ten-year review. *Advanced Engineering Informatics*, 47, 101245. https://doi.org/10.1016/j.aei.2020.101245

Zou, Y., Weinacker, H., & Koch, B. (2021). Towards urban scene semantic segmentation with deep learning from LiDAR point clouds: a case study in Baden-Württemberg, Germany. *Remote Sensing*, 13(16), 3220. https://doi.org/10.3390/rs13163220