Open Source Deep Learning Solutions for the Classification of MMS Urban 3D Data

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Abstract

Recent efforts on geospatial data processing showed a good potential for machine learning, particularly deep learning, tools in the automatic semantic interpretation of a 3D scene. Machine understanding of the surrounding environment is of great importance for several applications, including in particular the development of effective autonomous vehicles. Focusing on the specific case of autonomous driving vehicles, this work considers the problem of automatic segmentation and classification of urban point clouds. To be more specific, this paper considers a mixed approach, where, once properly removed ground points, 3D data segmentation is based on the Euclidean distance, whereas the classification of objects is based on a two-step procedure: first, PointNet++ is used for an initial soft-classification. Then, classification probabilities outputted by PointNet++ are used in combination with some additional geometric features extracted from the point cloud as inputs for a Random Forest classifier. The proposed approach is tested on a dataset collected in Sesto Fiorentino (Italy), showing quite promising performance. Interestingly, the employed tools are available as open-source software.

1. Introduction

3D data acquisition, processing and management are fundamental tasks in many applications, ranging from Geomatics to Robotics, Virtual Reality, Cultural Heritage and Autonomous Driving (Blaszczak-Bak et al., 2024; Fernandes et al., 2021; Conti et al., 2024). Thanks to recent technological advancements in sensors and processing techniques, recent systems allow to quickly acquire huge amounts of 3D data, using both photogrammetry and mobile laser scanning (Dominici et al., 2016; Masiero et al., 2018; Toschi et al., 2015; Aminti et al., 2022; Aricò et al., 2023; Tucci et al., 2018). In this scenario, point clouds play a key role, being the *raw 3D information* provided by both photogrammetry and laser scanning. Automatic understanding of such raw data typically involves the use of semantic segmentation tools (Hu et al., 2020; Guo et al. 2018; Pellis et al., 2022; Fiorini et al., 2024).

Focusing on the mobile laser scanning case, MMS (Mobile Mapping System) solutions allow real-time dense point cloud reconstruction (up to millions of points per second (Wong et al., 2021) of the surrounding environment during the acquisitions, i.e. while the acquisition platform is moving, thanks to the use of high-end remote/proximity sensing and localization sensors such as GNSS (Global Navigation Satellite System) and IMU (Inertial Measurement Unit).

Similarly to MMS, self-driving vehicles are provided with both localization and remote sensors, despite usually being cheaper with respect to those used in MMS. Considering autonomous driving, the quest for precise and reliable perception systems and accurate localization remains at the forefront of the required technological advancements (Levinson et al., 2011). Information extraction from point cloud data garnered from state-of-the-art LiDAR (Light Detection and Ranging) sensors, stands as a crucial enabler for understanding the complexity of a vehicle's spatial neighbourhood. Modern mobile laser scanning systems allow to obtain accurate, high-resolution, and geo-referenced descriptions of a vehicle's surrounding environment independently from lighting and weather conditions (Wu et al., 2018), making this kind of systems well suitable in a wide range of operating conditions and hence quite ideal for being used in self-driving vehicles, where the autonomous driving system is supposed to work in any (or almost any, depending on the automation level) scenario.

To be more specific, the employment of LiDAR technology in autonomous driving applications regards two levels of development. The first level regards its contribution to the vehicle's positioning system: indeed, LiDAR can be used in order to generate HD-maps and to support determining the vehicle location, both relative to its previous positions and with respect to a previously generated map (Wen et al., 2019). This aspect is of particular interest whenever the vehicle needs to move in a challenging scenario for the GNSS. Secondly, LiDAR can be effectively used for real-time sensing the surrounding environment, to obtain a proper interpretation of the vehicle's neighbourhood, e.g. detecting objects and persons (Wu et al., 2023).

A suitable interpretation of the surrounding environment usually requires the execution of the following activities: 3D data acquisition, 3D point cloud segmentation, object detection and classification (Li et al., 2022). Given the high acquisition rate, LiDAR datasets are usually voluminous. While providing a proper interpretation of the environment from LiDAR data is useful both for generating HD-maps and for the real-time tasks in autonomous vehicles, when considering the latter data understanding can be even more complicated, because only an incomplete description of the objects is usually available. These factors (huge data size, incomplete object representations and real-time analysis) make obtaining effective segmentation of such data into semantically meaningful categories a formidable challenge.

As autonomous vehicles navigate diverse and unpredictable environments, the demand for robust point cloud segmentation algorithms led to the employment of Artificial Intelligence (AI)-based methods, such as Deep Learning (DL) approaches (Zamanakos et al., 2021). In an epoch of transportation innovation, the fusion of AI and autonomous driving technologies has ushered in a new era of mobility, promising safer and more efficient roadways. At the heart of this transformation lies DL, a paradigm-shifting subset of artificial intelligence that has emerged as a cornerstone for endowing vehicles with the cognitive abilities essential for navigating complex environments (Grigorescu et al., 2019). The application of DL algorithms finalized for segmentation, detection, and classification in autonomous driving led to several problems and challenges regarding data acquisition and DL models. Considering the data typically acquired by a mobile laser scanning system, the diversified point density (that depends on the distances between LiDAR sensor and objects), the noise, and the incomplete nature of mobile acquisitions all contribute to making point cloud understanding quite challenging (Kumar et al., 2019). At the same time, big data acquisition generates high computation and time-consuming effort during DL operations (Liu et al., 2019).

This paper presents part of the work developed within the Spoke 9 of the Italian National Sustainable Mobility Center (MOST), part of the NextGenerationEU plan. More specifically, it deals the development of effective strategies in order to properly extract information from MMS data, with the goal of supporting the automatic generation of HD-maps and the characterization of the road environment. To be more specific, the paper will present the results obtained by using some recently developed deep learning tools, such as PointNet++, for properly detecting several objects of interest in an ad hoc collected dataset, in the city center of Sesto Fiorentino (Florence, Italy).

The organization of the article considers in the second section the description of the work inside the context of the MOST project, then, the proposed workflow is presented in the third section, whereas the obtained classification performance on the MMS urban dataset of Sesto Fiorentino is shown in the fourth section. Finally, conclusions and some discussion on future developments and open scenarios are drawn in the last section, highlighting both the current and future contribution of deep learning open source solutions for MMS urban 3D data processing and the possible future scenarios and potential improvements.

2. Case study

Contemporary society is characterized by a continuous change in the urban context, where the experimentation of new green mobility and, more generally, sustainable solutions define the new territorial asset of modern towns.

In this scenario, the design and management of mobility is a topic that does not only involve transport systems but other multidisciplinary fields of research as well, including social studies and geographical and urban analysis. The MOST project starts from this holistic approach, and, with its 14 different Spokes, it aims at the development of inclusive and sustainable mobility solutions (Alberti et al., 2023). Spoke 9 is focused on Urban Mobility and addresses developing and implementing innovative solutions to improve urban mobility. Its goal is to integrate advanced technologies such as Artificial Intelligence and Big Data to optimise public transport and reduce traffic congestion. Key initiatives include developing intelligent transport systems (ITS), promoting sustainable means of transport such as electric bikes and scooters, and creating digital platforms for traffic management. Focusing the interest on urban analysis, this work offers a scientific contribution to Spoke 9, investigating the use of possible open-source solutions to automatically classify 3D point clouds of the urban environment, collected by MMS systems, allowing specialists the possibility to make faster low-cost transport and infrastructural analysis inside the city centers.

The first results of this research outlined acceptable initial results, based on the use of PoinNet++, with room for future improvements (La Guardia et al., 2024). While the approach in (La Guardia et al., 2024) was mostly based on an open-source implementation of PointNet++, this paper combines such network with an additional machine learning module, as described in the following section, leading to a remarkable improvement in the obtained classification results.

3. From raw 3D data to Classified objects

The solution adopted in this experimentation implemented open-source modules for 3D point cloud classification based on deep and machine learning algorithms. The classification process was applied to the 3D urban datasets collected in an MMS survey on the streets of Sesto Fiorentino (Italy). The MMS was an integrated system composed of a LiDAR (ChcNav AU20), an Inertial Measurement Unit (IMU), a GNSS receiver and a Ladybug5+ high-resolution panoramic camera. The path of acquisition allowed to collect a 3D geospatial dataset reasonably representing different urban geospatial conditions, e.g. low and high-density urban areas, parks, etc (Figure 1).

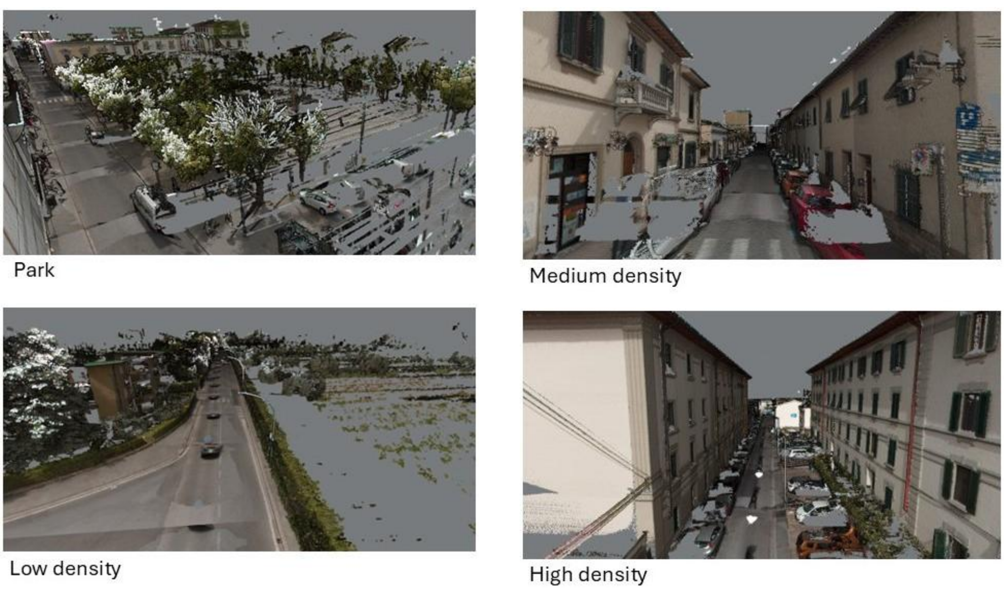

Figure 1. Different urban density areas collected in survey operations.

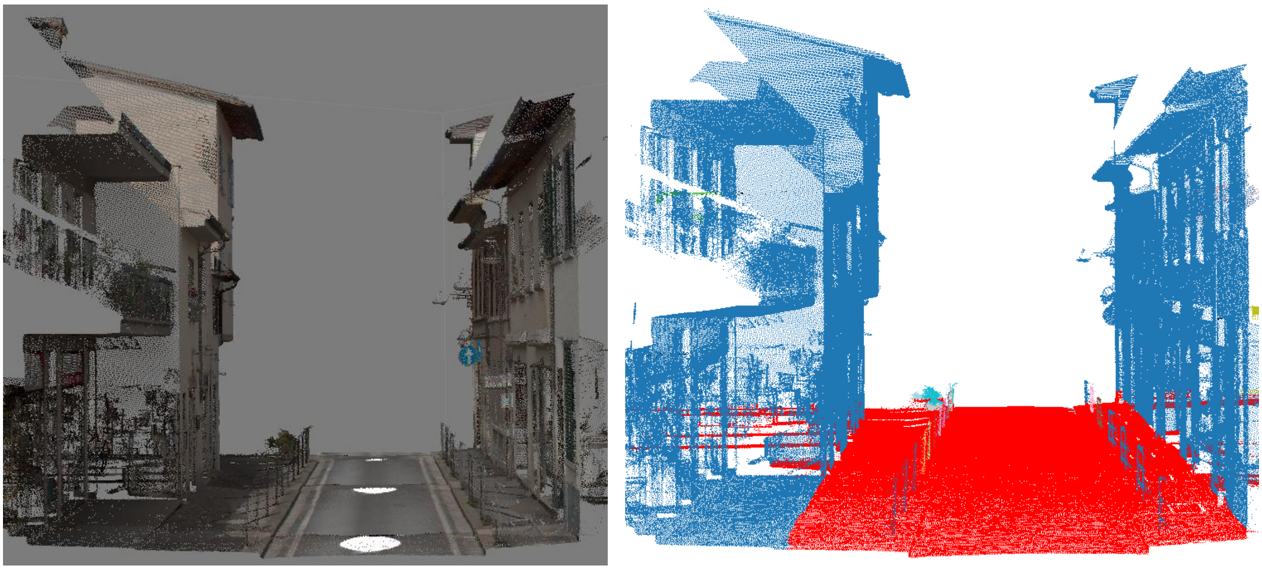

Figure 2. A subsampled portion of the MMS dataset (left), and the corresponding segmentation results (right).

First, the entire dataset was spatially partitioned in subsets, where each of them is composed by a point cloud of size 30×30×50 m. Additionally, each of such clouds was spatially uniformly subsampled at 0.025 m (Figure 2). Then, the point clouds were segmented employing freely available Python tools (Figure 3). To be more specific, the implemented segmentation approach is composed of two steps: 1) ground detection and removal, 2) Euclidian distance-based point clustering. Despite several tools can be used to implement such steps, first step was implemented by using a RANSAC (Random Sample Consensus)-based planar surface detection, and object clustering with Euclidean Cluster Extraction. The segmentation process was carried out using Open3D, NumPy and matplotlib open-source libraries using the Anaconda platform.

The use of RANSAC algorithm guarantees to identify, inside a 3D point cloud environment, a wide subset of inliers that fit a proper mathematical model considering a fixed tolerance, separating it from the outliers (Schabel et al., 2007; Yang et al., 2022). Given the typical regularity of road surfaces in urban environments, it can be effectively implemented to detect ground points in the considered dataset. Nevertheless, different methods can be used to improve the ground point detection performance in other working conditions (Zeybek et al., 2019). Large vertical (and horizontal) surfaces, typically building surfaces, were similarly detected and removed as well.
Then, off-ground points are clustered in different objects by applying Euclidean Cluster Extraction (Liu et al., 2021), i.e. segmenting objects based on their Euclidean inter-object distance. Such segmentation is clearly computationally quite effective, while not optimal in certain conditions. For instance, depending on the chosen threshold distance, different objects very close to each other could be clustered together.

The workflow, proposed for processing each of the subsets extracted from the overall dataset, is summarized in Figure 3.

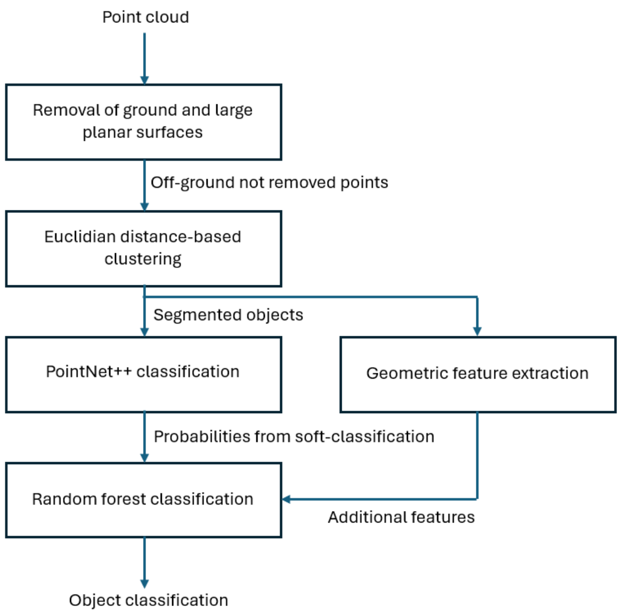

Figure 3. Proposed workflow.

The segmentation process was carried out using Open3D, NumPy and matplotlib open-source Python libraries. The final script was applied using Anaconda platform integrating the entire segmentation process in a single script file (Figure 4).
The combination of the mentioned algorithms allowed to quite quickly automatically separate ground, building surfaces, and most of the remaining objects.
Initial object classification was performed by analyzing the previously segmented objects with the PointNet++ neural network, employing an open-source version of such network developed in Python, compliant with Pytorch libraries (Yan et al., 2021).

```python
import open3d as o3d
import numpy as np
import matplotlib.pyplot as plt

# Load the point cloud from a PCD file
pcd = o3d.io.read_point_cloud("name_of_the_input_file.pcd")

# Step 1: Remove the dominant plane using RANSAC
plane_model, inliers = pcd.segment_plane(distance_threshold=0.28,
                                         ransac_n=3,
                                         num_iterations=1000)

# Extract point clouds of inliers and outliers of the dominant plane
inlier_cloud = pcd.select_by_index(inliers)
outlier_cloud = pcd.select_by_index(inliers, invert=True)

# Optional: visualize the point cloud after removing the dominant plane
inlier_cloud.paint_uniform_color([1.0, 0, 0])  # Red for the plane
outlier_cloud.paint_uniform_color([0, 1.0, 0])  # Green for the rest
o3d.visualization.draw_geometries([inlier_cloud, outlier_cloud])

# Step 2: Perform Euclidean Cluster Extraction on the outlier points
with o3d.utility.VerbosityContextManager(o3d.utility.VerbosityLevel.Debug) as cm:
    labels = np.array(outlier_cloud.cluster_dbscan(eps=0.95, min_points=100, print_progress=True))

# Optional: print the number of clusters
max_label = labels.max()
print(f"point cloud has {max_label + 1} clusters")

# Optional: visualize the clustered point cloud
# create a color map for visualizing different clusters
colors = plt.get_cmap("tab20")(labels / (max_label if max_label > 0 else 1))
colors[labels < 0] = 0  # Set color to black for noise points
outlier_cloud.colors = o3d.utility.Vector3dVector(colors[:, :3])
o3d.visualization.draw_geometries([outlier_cloud])

# Optional: save the segmented point clouds with cluster labels
o3d.io.write_point_cloud("pc1.pcd", inlier_cloud)
o3d.io.write_point_cloud("pc2.pcd", outlier_cloud)

# Optional: further process each cluster by selecting points with the same label
for i in range(max_label + 1):
    cluster_cloud = outlier_cloud.select_by_index(np.where(labels == i)[0])
    o3d.io.write_point_cloud(f"pc2{i}.pcd", cluster_cloud)
```

Figure 4. Example of simple Python script for point cloud segmentation.

The algorithm, initially evaluated for classification using the ModelNet10/40 dataset (comprising multiple categories of generic 3D objects) was adapted to ensure compatibility with an external 3D point cloud dataset. The training and testing datasets were structured to include typical object classes of interest in the urban environment. In particular, eight classes were considered: barriers, cars, motorcycles/bicycles, pedestrians, pillars, light poles, traffic signs, and trees (Figure 5).

The training dataset was partially derived from point clouds extracted from the Sesto Fiorentino dataset, and partially from data originated from other datasets, obtained through Mobile Mapping System (MMS) acquisitions, publicly available (Bayrak et al., 2024; De Deuge et al., 2013). Conversely, the testing dataset was exclusively composed of objects extracted only from the Sesto Fiorentino dataset.

To ensure the effective application of the algorithm, each point cloud within the dataset was pre-processed according to some specific criteria. In particular, the point cloud data was customized in order to include only positional coordinates (x, y, z) and the corresponding normal vectors (Nx, Ny, Nz) for each point.

Additionally, uniformity in the number of points per cloud was maintained, with each point cloud standardized to contain exactly 1000 points. This standardization was achieved through automated oversampling or subsampling procedures using dedicated Python scripts.

The classification process was optimized to enhance classification accuracy while mitigating the risk of overfitting and reducing computational processing time (Table 1).

Training and testing datasets were significantly larger with respect to (La Guardia et al., 2024), as shown in Table 2.

Random forest was implemented using as inputs 1) the classification probabilities outputted by PointNet++ and 2) additional geometric features extracted from the object point clouds. To be more specific, in this implementation just features related to the point cloud sizes were considered. 100 prediction trees were used in the Random forest classifier.

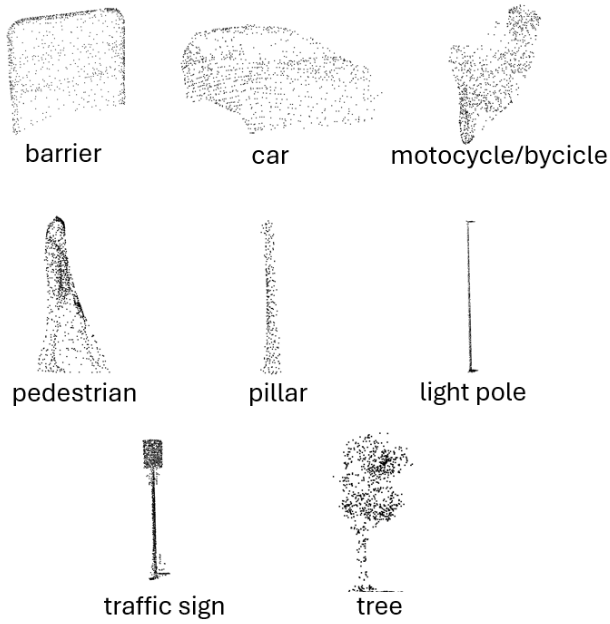

Figure 5. Object classes considered in this work.

PointNet++ parameters	train	test
Batch size	8	24
Epochs	200	n
Point number	1000	1000
Learning Rate	0.001	n
Optimizer	Adam	n
Decay Rate	0.0001	n

Table 1. Parameters adopted in PointNet++.

dataset	training	testing
Barrier	59	51
Car	56	60
Motorcycle/bicycle	46	41
Pedestrian	79	51
Pillar	56	41
Light pole	63	42
Traffic sign	38	46
Tree	35	44

Table 2. Objects in the training and testing dataset.

4. Results and discussion

The classification results shown in this section distinguish between two cases: the use just of PointNet++ (A) and its combined use with Random Forest (B). The results are shown in Figure 6 for case (A), and Figure 7 for (B). Results are shown as percentages, normalized with respect to the number of objects in the real categories. Results refer to the test dataset of Table 2.

Once trained with at least 35 object samples per category (see Table 2, column “training”) PointNet++ allows to obtain quite decent results (Figure 7), even if with some errors, in particular misclassifying cars as motorcycles/bikes, poles as traffic signs, and traffic signs as pedestrians or pillars. Overall classification accuracy (total number of correct classifications/number of objects) was 81.1% (approach (A)).

Instead, in approach (B) 99.5% overall accuracy was reached, with few errors mostly misclassifying cars as motorcycles, motorcycles as traffic signs, and trees as motorcycles. Results in case (B) were much better than in case (A), with few elements outside of the main diagonal.
Despite the quite apparent improvement from (A) to (B), it may be possible to further reduce the remaining errors by introducing some other geometric feature in the Random Forest-based classification process.

		real label							
		barrier	car	motorcycle bicycle	ped	pillar	pole	traffic sign	tree
predicted label	barrier	100,0	6,7	0,0	0,0	0,0	0,0	0,0	0,0
	car	0,0	58,3	0,0	0,0	0,0	0,0	0,0	0,0
	motorcycle/bicicyle	0,0	30,0	90,2	3,9	0,0	0,0	0,0	2,3
	pedestrian	0,0	1,7	9,8	84,3	2,4	0,0	15,2	2,3
	pillar	0,0	0,0	0,0	9,8	97,6	0,0	15,2	0,0
	pole	0,0	0,0	0,0	0,0	0,0	61,9	2,2	0,0
	traffic sign	0,0	0,0	0,0	2,0	0,0	38,1	67,4	0,0
	tree	0,0	3,3	0,0	0,0	0,0	0,0	0,0	95,5

Figure 6. PointNet++ classification results: percentages, normalized with respect to the number of objects in a real class.

		real label							
		barrier	car	motorcycle bicycle	ped	pillar	pole	traffic sign	tree
predicted	barrier	100,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
	car	0,0	98,3	0,0	0,0	0,0	0,0	0,0	0,0
	motorcycle/bicicyle	0,0	1,7	97,6	0,0	0,0	0,0	0,0	2,3
	pedestrian	0,0	0,0	0,0	100,0	0,0	0,0	0,0	0,0
	pillar	0,0	0,0	0,0	0,0	100,0	0,0	0,0	0,0
	pole	0,0	0,0	0,0	0,0	0,0	100,0	0,0	0,0
	traffic sign	0,0	0,0	2,4	0,0	0,0	0,0	100,0	0,0
	tree	0,0	0,0	0,0	0,0	0,0	0,0	0,0	97,7

Figure 7. PointNet++ followed by Random Forest classification results: percentages, normalized with respect to the number of objects in a real class.

It is worth noting that, while in this work the segmentation and classification tasks were considered separately, several recent works considered semantic segmentation as a unique step, often implementing directly PointNet++ or other recently developed networks to such aim (Zhao et al., 2021). Despite our current results in this direction are less worthy than those obtained with the presented procedure, our future work will also be dedicated to further investigation on the joint solution of segmentation and classification problems.

5. Conclusions

This work considered the problem of segmenting and classifying urban point clouds, acquired using proper MMS platforms. The proposed approach was based on separately implementing such two steps. While such a separate solution is different from some joint strategies, implemented in some recent semantic segmentation works, it still allowed to obtain quite solid classification results.
To be more specific, first, ground and large planar surfaces were detected with RANSAC and removed from the point cloud. Then, best classification results were obtained on the considered urban dataset, collected in Sesto Fiorentino (Italy), by combining the use of PointNet++ and Random Forest, where the latter has been applied using as inputs the soft-classification probabilities outputted by the first and some additional geometric features, related to the size of the objects. Overall, the implemented procedure is quite fast and effective.
Future investigations will be dedicated to checking the performance of the proposed approach on a larger object dataset and investigating the development of alternative approaches, i.e. based on semantic segmentation implemented as a single step procedure.

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