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Semantic Enrichment for Rooftop Modeling using Aerial LiDAR Reflectance

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***Abstract*—As demanded by smart city applications, the recognition and enrichment of urban semantics from unstructured spatial big data became an emerging trend for the development of building information model (BIM) and city information model (CIM). Rooftop constructs the essential part of BIM and CIM and loads various new application practices and scenarios. The recognition and enrichment of rooftop elements represent the trending requirements. This study develops a new approach for semantic enrichment of aerial Light Detection and Ranging (LiDAR) point clouds. In this paper, machine learning models such as decision tree are applied to predict green roof elements based on the geometry and laser reflectance, and was validated in a pilot zone in the main campus of The University of Hong Kong. The recognized rooftop elements could provide a solid foundation for further research, such as rooftop landscape, rooftop energy, rooftop farming.**

Keywords—Rooftop, building information model, city information model, LiDAR reflectance, decision tree

I. Introduction

In the era of smart cities, rooftops have gone far beyond their traditional functions to increasingly become the focal point for more intriguing uses. This is particularly in high-density urban areas. For example, in Hong Kong, rooftops are increasingly part of discussions about solar energy farming, urban agriculture [1], community connection, and open space [2]. These applications of rooftops could benefit from the availability of digital rooftop models with rich semantics. Semantically-rich rooftop models enable visualization and simulation, based on which more informed decision could be made in order to make use of rooftop spaces. Therefore, the recognition and enrichment of semantics, e.g., category, materials, functions, of rooftop elements, is a trending theme.

Nevertheless, semantic enrichment for rooftop modeling is still a challenging problem. Manually complementing and modeling the rooftop details are extremely expensive, tedious, and hampered by accessibility problems. Automatic or semi-automatic object recognition of photos and 3D point clouds, the rooftop elements can form the uppermost part of the created BIM or CIM. However, the current enrichment practice of semantics, especially those non-geometric semantics, of rooftops, are unsatisfactory. More solid methods should be developed for developing semantically-rich rooftop models.

This study aims to utilize the reflectance, a physical property that denotes how much of laser beam is reflected by an object's surface materials. Reflectance is also a standard data property of every point in the Log ASCII Standard (LAS) format of LiDAR (Light Detection and Ranging), for rooftop element recognition and semantic enrichment. It extends previous research work that reconstructs the geometries of rooftop elements by using point clouds [2]. In this paper, the laser reflectance is introduced as a key feature for rooftop element classification and semantic enrichment. Decision tree, a typical machine learning model, is applied to classify the rooftop elements using laser reflectance and geometric features (e.g., area and height of the rooftop element).

The contributions made by this study are two-fold. Firstly, this study suggests that reliable urban object recognition requires non-geometric information beyond the spatial data. Second, this study confirms that laser reflectance can be an important data source for recognizing and enriching the urban semantics of rooftop elements.

The remainder of this paper is organized as follows. Section II reviews the related methods. Section III describes our semantic enrichment approach. A pilot case is introduced in Section IV, and the experimental results appear in Section V. Conclusion is given at the end of the paper.

II. Literature Review

Many methods, including data clustering, region growing, energy minimization (optimization), and model fitting, have been developed to automate the recognition of the semantics of building rooftops from 3D point clouds [3], [4]. Reference [5] proposed a two-step method to segment and form rooftop boundary from raw boundary data extracted from point clouds. Reference [6] proposed an enhanced probability density clustering algorithm to cluster

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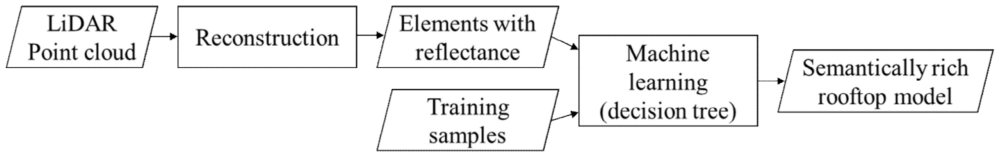
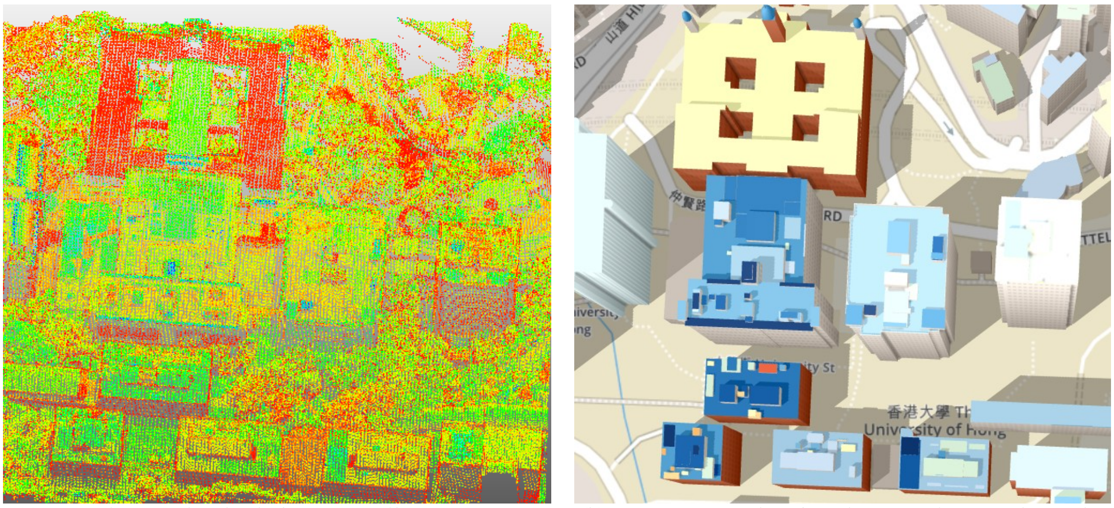


Fig. 1. The overall framework of the proposed approach



(a) Input LiDAR point cloud of 55,000m² pilot area (298,126 points), where color indicates the laser reflectance (warmer = less)

(b) 158 reconstructed rooftop elements using [2], where color indicates average reflectance (warmer = less)

Fig. 2. The input LiDAR data and reconstructed rooftop elements with reflectance

the rooftop primitives by taking into account the topological consistency among primitives. Then, it employed a new Voronoi subgraph based algorithm to trace the primitive boundaries seamlessly. Reference [7] provided an interpolation of rooftop area in which multi-surfaces intersect generating non-manifold points. Reference [8] proposed a triangle geometry method to help reconstruct virtual roofs using point cloud data. Reference [2] employed architectural regularity to fine-tune the recognized identified rooftop elements with the building footprint.

Generally, these methods not only are capable of creating complex building models but also, they can be applied for the simulation of any roof styles including curved and freely formed roofs. Nevertheless, the quality of raw data influences the model reconstruction extremely, such as the sensitive impact from the point density, noise and outliers. Besides, the non-geometric semantic enrichment from point clouds is still challenging [9]. As a result, the semantics, e.g., category, materials, functions, in the reconstructed models, are unsatisfactory.

III. Overview of Proposed Method

This paper aims to utilize the LiDAR reflectance, and apply a machine learning-based semantic enrichment for rooftop modeling. The value of laser reflectance can often the albedo approximately, because many aerial LiDAR uses ultraviolet (e.g., 340nm), vis, or near infrared laser beams [10]. Laser reflectance, as well as the derived albedo, offer vital semantics about the surface, type of objects, and possible functions. Fig. 1 shows the overall framework of the proposed approach. The reflectance is an innate property of each laser-measured point, e.g., the property “Intensity” is reserved for reflectance in the LAS (ver. 1.4) format. By associating the reconstructed rooftop elements and a small set of training example, the machine learning models in the proposed approach can predict new semantics, e.g., type of green roof elements, materials, and functions, to enrich the reconstructed geometric rooftop models to a semantically rich one.

Decision tree is a popular machine learning model, and easy to interpret to human experts [11]. Various decision tree models have successfully been trained and applied in many research areas such as radar signal classification, character recognition, remote sensing, medical diagnosis, and expert systems. The most significant feature of a decision tree is the ability to decompose a complicated decision process into a collection of a more straightforward decision. As shown in Fig. 1, this study applies the decision tree to predict the semantics via classification based on their geometric and reflectance features.

IV. A Pilot Case in Hong Kong

This study selects an area of The University of Hong Kong. Totally, ten buildings at the center of the campus area were selected for the case. There are three main reasons for the selection. Firstly, the selected area is small but resides tens of various buildings, ranging from Edwardian style to post-modern style, from low-rise to high-rise, and with the year of built from the 1910s to 2010s. Secondly, the results can be compared to previous studies, such as [2], [5], and [8]. The last concern was about privacy and data ownership.

Fig. 2a shows the input LiDAR point cloud of 298,126 points as a part of the aerial survey done by [12]. The reflectance in Fig. 2a was measured between 400-2000 nm wavelength range, where the warmer color indicates less reflectance; Fig. 2b shows 158 small rooftop elements reconstructed using [2], where the blue color shows a high reflectance and the yellow color shows a low reflectance. Based on the observation and news reports, three areas of green roof elements (of 7 rooftop elements), were assigned to the training examples. In Fig. 2, there was only one low-reflective roof, of which the building is the Main Building, a built heritage (built in 1911) in Hong Kong.

The task of semantic enrichment in this paper is thus to classify the green roof elements from the rest reconstructed geometric primitives. In addition, two specific types of green roof elements are distinguished in the pilot case: (i) turf on which vegetation covers the whole surface of the roof elements, and (ii) potted area on which plants live in pots or other small containers. Table 1 lists an excerpt of the summarized data table of the pilot case for roof element classification and semantic enrichment. The data columns in Table 1 include average reflectance in percentage, the top area of each element in square meter, height (top surface above the registered building roof level in government's digital map) in meter.

TABLE I. EXCERPT OF THE DATA TABLE OF THE PILOT CASE FOR CLASSIFICATION AND ENRICHMENT

Label	Avg. reflectance (%)	Top area (m^2)	height (m)
Non-green	54.5	123.6	2.47
Non-green	53.6	66.2	2.39
Non-green	36.7	400.5	3.53
Non-green	34.6	58.6	3.52
Non-green	50.8	12.5	2.84
Non-green	29.5	5.0	0.80
Non-green	30.5	9.5	0.72
Non-green	33.5	29.1	0.63
Non-green	28.1	5.3	0.72
potted	35.1	74.0	0.35
turf	54.9	61.9	–0.35
turf	53.7	529.3	–0.34
turf	50.4	74. 4	–0.39

The computational experiments were conducted on a Windows 10 desktop PC. The decision tree is offered by the *rpart* package (ver. 4.1), which is freely available on the *R* platform (ver. 3.4). The parameters of the decision tree are: "min split = 2," "max depth = 5," and "min bucket = 1."

V. EXPERIMENTAL RESULTS

5.1 The trained decision tree model

Fig. 3 shows the rooftop elements recognition processed by the decision tree, which used less than 0.01s to get the final accurate results. It can be found that the target attribute in the root node is the "non-green"; the first level condition is "height ≥ −0.18m"; the second level is "area < 71m²"; the third level is "height ≥ 0.96m"; the fourth level is "height

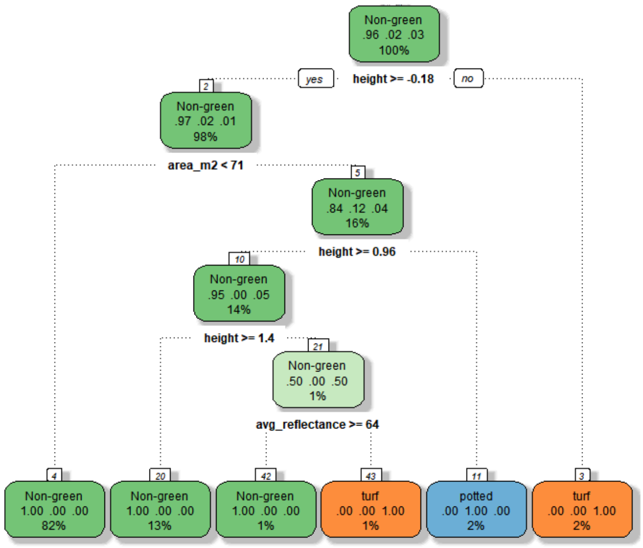


Fig. 3. A decision tree model trained in less than 0.01s

≥1.4m"; and the fifth level is average "reflectance ≥ 64%". Overall, the "potted" elements are distinguished by selecting attribute between "0.96m ≤ height < 1.4m" and "area ≥ 71m²." There are two rules embedded in Fig. 3 that lead to "turf" elements. One rule is height < −0.18m; the other is "height ≥ 1.4m" and "area > 71m²" and "average reflectance ≥ 64%".

5.2 Semantic enrichment of green roof elements

Fig. 4 shows the comparison of predicted green roofs and mesh models on Google Maps. The screenshot of the mesh models on Google Maps illustrates the real distribution of rooftop elements. The green areas, located mainly on top of three buildings, are corresponded with the predicted green roof elements. The semantic enrichment of green roof from reflectance makes up the shortcoming of incomputable Google's mesh model even though they have details. The comparison result shows the expecting accuracy for the elements detection and division.

(a) Prediction results (dark green = turf, light green = potted) (b) Screenshot of the mesh models on Google Maps

Fig. 4. Comparison of predicted green roofs and the mesh models on Google Maps

5.3 Discussion

In comparison to previous results such as [3] and [5-8], the proposed method has several advantages. Firstly, it overcomes the drawback of the low quality of raw data, such as the sensitive impact from the local point density, noise and outliers. Second, it introduces laser reflectance as a key factor for rooftop elements recognition. As a result, the semantics, e.g., category, materials, functions, in the automatically reconstructed BIM/CIM would be more satisfied than traditional methods.

However, there also are some limitations in this paper. This study used five-level attributes and limited data for the small area detection, but this division technique and limited scale of training data might not accurate enough when applying it to city-scale rooftop elements recognition. The sample data of the training may, therefore, require manual debugging as the test area increases. In addition, the range of detected green areas is mainly divided by rectangles. However, many roof green areas may exhibit a distribution of irregular patterns.

VI. Conclusion

A new criterion to rooftop elements recognition from LiDAR data is proposed. The statistical fluctuations of the laser reflectance, which roughly reflects the reflectance, is proven successful for recognizing non-geometric characteristics of rooftop elements. This study contributes to the importance of non-geometric information regarding reliable urban object recognition and confirms that laser reflectance can be an important data source for recognizing and enriching the urban semantics of rooftop elements. This proposed method can overcome the shortcomings of traditional recognition methods and increases detection accuracy. In addition, the method overcomes the drawback of the quality of raw data, such as the sensitive impact from the local point density, noise and outliers. As a result, the semantics, e.g., category, materials, functions, in the automatically reconstructed BIM/CIM would be more satisfied than traditional methods. The proposed utilization of laser reflectance can also be helpful in BIM/CIM research for indoor scenes and city areas. Further research could focus on the widening of technique application scenarios, semantic evidences such as architectural symmetry [13], and the increasing of recognition accuracy in large-scale areas.

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