Automated Object Extraction from MLS Data: a Survey

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Abstract—**Realistic 3D city modeling using Mobile Laser Scanning (MLS) technique experienced a remarkable revolution in aiding urban planning, regulation design, city management, navigation, and emergency responses. This paper focuses on thoroughly examining the advance of automated MLS object extraction techniques over the last five years. Categorized as either on-road or off-road, mainly six objects are included in this paper (road curbs, road markings, pavement cracks, building facades, pole-like objects and trees). MLS extraction techniques applied on typical objects is evaluated according to their method design, degree of automation, precision, and computational efficiency. Recent researches mostly focus on developing accurate object extraction algorithms and most of the reviewed methods can achieve high precision; however, optimizing the trade-off between computational cost and accuracy remains a big challenge. In addition, there is still no general standardized approach to deal with MLS objects extractions to date; most algorithms reviewed in this paper still need some artificial interference to ensure accuracy and efficiency.**

Keywords-MLS technique; automatic algorithm; object extraction; literature review

I. INTRODUCTION

In recent years, laser scanning technology has led to the integration of laser scanners, navigation sensors, and other data acquisition sensors with mobile mapping platforms [1]. Mobile laser scanning (MLS) has become a cost-effective solution for capturing vary dense point clouds that can be used for realistic 3D city modeling.

To some extent, urgent demands in realistic 3D city modeling bloom the development of reliable data [2]. This paper reviews object extraction techniques using mobile laser scanning (MLS) data that are automated or semi-automated. We categorize them based on the existence of human intervention during the process. Fully automatic extraction does not require any input or adjusting on parameter during data processing. On the other hand, semi-automated object extraction process requires users to set different thresholds according to different situations and output quality.

Minimizing manual processing meanwhile retaining high precision and efficiency are the ultimate goal for object extraction techniques. This review thoroughly examines the implementation of both road and off-road objects extraction techniques by using MLS data. It includes in-depth descriptions of methods, assessments of extraction quality and explanations of the existing challenges. The review examines both automated and semi-automated techniques. We review recent 5-year work undergone in this field. Given the limited progress in this early-stage research area, to date there is a strong growing interest in speeding up the development.

II. ROAD OBJECT EXTRACTION

Extracting objects from MLS data can be categorized into two streams: road and off-road objects. This section reviews techniques for extraction of road objects about road curbs, road markings and pavement cracks.

MLS data is first developed in use of road and lane detection purposes. By the aid of the MLS 3D information, most of the new algorithms have mainly focused on road condition monitoring and road object detection.

A. *Road Curbs and Edges*

All of the current MLS curb extraction methods are mainly based on three strategies: 1) detecting planer surfaces, 2) detecting linear elements, 3) determining 3D spatial relationships.

Non-curb points were first roughly removed based on a certain height constraint in [3]. The remaining curb-alike points were implemented a surface growing segmentation algorithm in order to segment raw curb points into layers. A sigmoidal function is then fitted near the polygonal chain to increase the accuracy. Only two parameters were required in the whole algorithm; one is the defined height threshold; another is a slope parameter. The validation of the proposed algorithm revealed a completeness rate ranging from 54% to 83% and a correctness rate as 90%. The major concern of the relatively low completeness is due to the block of vegetation and vehicles on road.

978-1-4673-9323-2/15 $31.00 © 2015 IEEE
DOI 10.1109/ISKE.2015.35

Similarly, An automated curb detection algorithm was proposed in [4] by forming pseudo scan-lines that easily indicate the surface elevation change to represent road surface. Curbs are detected based on both sharp elevation jump and a defined elevation threshold. The computation cost for processing data covering a 25 m long road section was around 40s. The proposed algorithm achieved an accuracy of 8 cm in horizontal and 2 cm in vertical.

A semi-automated curb extraction algorithm introduced in [5] examines road properties in both large-scale and local scale. parameters are critical for the performance of the method. A moving window operator was applied to detect local changes to locate curb points. The proposed selection of parameters resulted in high completeness and correctness rates which both exceeded 95%. But it may be lack of confidence in detecting noisy road boundaries. The advantage in [5] is its capacity for handling large-scale point clouds without use of trajectory data or 2D maps.

Road curbs extraction in [6] was under the aid of 2D road network map. 2D attractor maps were created from the 3D sub-point clouds. Ribbon snake model was implemented onto attractor maps to detect curbstones. This study combined both ALS and MLS data to create large-scale city modeling. The curb detection used 24 hours to complete computation of the entire point cloud. It achieved 86.3% correctness and 81.8% completeness with the capacity of detecting bridges, tunnels, and other kinds of roads.

A novel method for estimating earthwork volumes in asphalt pavement reconstruction was presented in [7]. By using curb-based method in [4], road surface points are detected and then divided into a set of blocks perpendicularly partitioned into grids, where two surface features are extracted using the RANSAC. Finally, the volume of each grid is calculated according surface features. The proposed method achieved a millimeter-level accuracy in estimating asphalt road thickness and outperform the traditional surveying methods.

B. Road Markings

Extracting road markings directly from 3-D mobile LiDAR point clouds is a very challenging task. In most cases, road markings have higher reflectivity against scanners than road surfaces; therefore road markings have higher density than the surrounded road surfaces. By using the retro-reflective property, an automated algorithm based on range dependent thresholding function and binary morphological operations was proposed in [8]. This method can effectively extract road markings, but for those markings in circles or words, the accuracy is not desirable.

Indeed, most algorithms used to extract road markings are based on the prior semantic knowledge of shapes of most road markings and their unique retro-reflectivity against surroundings within a range. A method put forward in [9] can automatically extract road markings from MLS point clouds by using a range as a significant standard in segmentation. This method firstly isolate road surfaces against off-road objects by a interpolation in geo-referenced feature imagery and a height threshold within a range, then the road markings can be extracted by using the prior semantic knowledge. Unique intensity attributes of road markings were also taken in [4] to present an automatic algorithm to extract road markings. Off-road objects were firstly removed, and then extended Inverse Distance Weighting (IDW) interpolation method was used to generate geo-referenced intensity images. Then gray-values were calculated in each grid in geo-referenced images. And finally, the morphological operation is applied with prior knowledge of road marking shapes to extract road markings.

Extracting road markings by 2-D geo-referenced feature images may lead to incompleteness and incorrectness in feature extraction. road markings are directly extracted from road surface points through multisegment thresholding and spatial density filtering in [10]. the geospatial information of the road markings is preserved and can be used in other applications. Time complexity analysis showed that the proposed method can handle large volumes of mobile LiDAR point clouds in a short time. Through quantitative evaluation, the proposed method achieved an average completeness, correctness, and F-measure of 0.93, 0.92, and 0.93, respectively. However, the limitation of the proposed method exists in the classification of dashed centerlines and dashed boundary lines when handling curved roads.

C. Pavement Cracks

An iterative tensor-voting algorithm was proposed in [11] to detect pavement cracks using MLS data. The geo-referenced images were converted from road MLS points using the extended IDW interpolation. This method took both elevation and point intensity into account when interpolating road points. The iterative tensor voting based crack detection achieved completeness as 96% and correctness as 85%. It could well detect road cracks with width larger than 2 cm. The computational time is considerable which mainly consumed by the iterative tensor voting process. However, it could be solved in the research of distribution computation because the voting process of each tensor is independent.

Extracting crack skeletons in [12] uses intensity information of cloud clouds to identify pavement cracks that usually exhibit lower intensities compared to their surroundings. crack candidates are extracted by applying the Otsu thresholding algorithm and crack skeletons are extracted based on an L1-medial skeleton extraction method. the proposed algorithm was executed very fast and performs very well in extracting 3D crack skeletons.

III. OFF-ROAD OBJECT EXTRACTION

Apart from on-road objects, detection and reconstruction of off-road objects also become hot topics in recent years.

A. Building Facades

Points on buildings have height property, thus most methods can use height information to segment buildings. A semi-automated algorithm was introduced in [13] to extract building facade footprint by using RANSAC technique. Projecting all the points on buildings to different planes firstly and then by using PCA, points on planes are selected. Finally, the footprint on building facades can be determined.

This method can effectively decrease the influences caused by noise or other objects, but it cannot achieve desirable accuracy for those buildings that have complex structures.

An algorithm based on the coordinate information contained in geo-referenced 3D point clouds was also introduced in [14]. This algorithm computed the 3D horizons of all the points, and then by computing different slope and aspect angle corresponding to each point, the building facades can be successfully classified. This algorithm also develops a workflow to detect the interior wall. However, for those buildings under shadows of trees, this algorithm cannot work as expected.

In most cases, the large size of MLS data increases the difficulties to be processed automatically. An automatic processing algorithm was applied in [15] to detect building facade by choosing intelligent seed point. This method firstly used RANSAC technique to achieve segmented planar patches, and then introduce intelligent seed points and growing rules to detect important specific building facade objects, finally, a rule based partitioning tree is applied to recognize the designated objects. This algorithm decreases the complexity for computing abundant data by separately processing the tested point clouds step by step.

In addition, some algorithms are developed not only to detect but also to reconstruct facades. A semi-automated algorithm was put forward in [16] to reconstruct building facades by fusing MLS data and images. The method is based on a prior sematic knowledge of objects on building facades. The large-sized point cloud was firstly segmented by a growing segmentation algorithm to planar planes. And each segment was processed by the defined constraints to determine the most likely object. This method works well except for windows, but by fusing close-range images with point clouds, the object detection accuracy can be improved.

B. Pole-like Objects

To extract pole-like objects, clustering or vertical growing is performed using the segmented points or voxels.

The clustering of segments was usually done in the same horizontal position in [17]. And the second phase clustering done in [18] used vertical growing. A seed point was picked and then a cluster was created. Nearest neighboring points were added into it and the cluster grew in vertical direction by setting a maximum allowed distance based on the actual scene.

In some cases, cluster merging is needed. For street lighting poles, the method of identifying clusters belonging to the same object is to calculate the horizontal distance of the centroids of clusters. Besides, some clusters contain more than one object so we need to segment these clusters[19]. Ncut segmentation method was introduced in [20] to partition the cluster into two segments correctly.

Laplacian smoothing was applied on segmented points in [21] to move each point towards the centers of the neighbors. According to the authors, this operation can effectively distinguish pole-like objects from others by removing the noise and simplifying the objects. It can improve the accuracy of point classification by using PCA which was their next step to classify the points and detect the points representing pole-like objects.

Further research can be put on extraction of concrete pole, like the street light pole. The algorithm that accurately extracts street light poles using a novel pairwise 3-D shape context was proposed in [19]. The results show that street light poles are robustly extracted with a completeness exceeding 99%, a correctness exceeding 97%, and a quality exceeding 96%. Besides, in [22] presents a 3-D object matching framework to support information extraction directly from 3-D point clouds. A locally affine-invariant geometric constraint is proposed to effectively handle affine transformations, occlusions, incompleteness, and scales.

C. Street Trees

Street trees have trunks that are also pole like objects, so the extraction method of trees is similar to poles. The same method was used in [23] as [21] to firstly detect all the poles and then spatial distribution of the detected objects was considered to further extract street trees.

A three stage extraction method was introduced in [24]. The coarse segmentation was done based on the DEM and CSM. And the revolving door (RD) edge estimation method was used in the medium scale stage to determine the edges of tree crowns. Rough 3D tree models can be generated from The RD-schematic algorithm. The ellipse fitting was performed for the crown edges and their symmetric analysis. This process was implemented to remove poles and walls.

A voxel marking process presented in [25] can model the location and geometry of trees. After segmentation on the 6th voxel layer, the algorithm searched top-down to the 1st layer and then bottom-up to the highest layer of the voxel grid to mark all the voxels that are potential tree parts. To mark a voxel, the competition was based on its distances to the seed voxels of different clusters. When the marking process finished, the morphological parameters for each cluster were calculated and poles were removed according to crown diameter and object height.

According to the dataset, the parameters used in [24] are needed estimation so the method is semi-automated. Preprocessing of the dataset may be needed to improve efficiency and accuracy at different situation. The evaluation results show that the completeness and correctness of the method in [25] for street tree detection are over 98%. Besides, morphological parameters of trees were calculated as useful additional information.

IV. CONCLUSION

Road object extraction often deals with large raw MLS point clouds. Handling large-scale point clouds usually involves partition or pyramiding of raw MLS points into computation-capable sub-clouds. reducing computational cost is not the current research focus in MLS field. Most attentions have been placed on developing precise object extraction algorithms. Most of the approaches reviewed here can achieve high precision accuracy. However, precision error increases as the size of point clouds increases.

Optimizing the trade-off between computational cost and accuracy is a big challenge in recent years. In addition, there is no such a general standardized approach to in deal with MLS object extractions to date. All the methods reviewed had some drawbacks to some extent. Due to the complexity and variety of urban objects, developing a fully automated extraction algorithm without manual aids is rather a challenge. Majority of proposed algorithms now still needs artificial interference to ensure final accuracies or correctness. Thorough studies in object extraction are needed in the future.

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