TURNING MOBILE LASER SCANNING POINTS INTO 2D/3D ON-ROAD OBJECT MODELS: CURRENT STATUS

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ABSTRACT

Traditional road surveying methods rely largely on in-situ measurements, which are time consuming and labor intensive. Recent Mobile Laser Scanning (MLS) techniques enable collection of road data at a normal driving speed. However, extracting required information from collected MLS data remains a challenging task. This paper focuses on examining the current status of automated on-road object extraction techniques from 3D MLS points over the last five years. Several kinds of on-road objects are included in this paper: curbs and road surfaces, road markings, pavement cracks, as well as manhole and sewer well covers. We evaluate the extraction techniques according to their method design, degree of automation, precision, and computational efficiency. Given the large volume of MLS data, to date most MLS object extraction techniques are aiming to improve their precision and efficiency.

Index Terms— Mobile laser scanning (MLS), 3D point clouds, object extraction, road

1. INTRODUCTION

Road information is very useful and important, as it is required by many applications, especially transportation applications. For example, transportation departments must frequently evaluate pavement conditions for road maintenance and rehabilitation [1].

To acquire road information, people must collect raw road data first. Traditional road data collecting methods rely largely on in-situ measurements, which are time consuming and labor intensive. By contrast, with a vehicle-borne Mobile Laser Scanning (MLS) system, people can precisely survey a large area of roads within a relatively short time regardless of ambient light conditions [2].

As the major component of a MLS system, laser scanners emit eye-safe laser pulses and receive the returns. Based on the return energy and the pulse travel time, the reflected intensity and the precise distance between the scanner and the object's surface are observed. These scanned data form high resolution geo-referenced 3D point clouds.

After the data collection, the remaining task is to extract information from the data. However, the data size of a point cloud is usually large and uneven in point density. Moreover, a point cloud usually is incomplete due to occlusion or limitation of the scanning position and angle. As a result, processing MLS data has been challenging. To date, most MLS object extraction techniques aim to improve their precision and efficiency.

MLS data may contain both on-road and off-road objects. This paper mainly focuses on examining the current status of automated on-road object extraction techniques from collected raw 3D MLS road point cloud data over the last five years. Those techniques for automated detection and extraction are presented as follows: Section 2 -- road surfaces; Section 3 -- road markings; Section 4 -- pavement cracks; Section 5 -- manhole covers.

2. EXTRACTION OF ROAD SURFACES

A curb is the edge where a raised road shoulder, sidewalk or road central reservation meets an un-raised roadway. Most urban roads have curbs. As a result, road surface extraction usually can benefit from curb detection. Automated extraction of curbs and road surfaces is extremely important for autonomous driving applications.

Techniques for extraction of road curbs from MLS data can be mainly summarized in three categories: 1) detecting planer surfaces, 2) detecting linear elements, and 3) determining 3D spatial relationships.

An algorithm to segment road points from raw MLS data using surface normal direction and normalized eigenvalues was proposed in [3]. Road curbs are extracted using both the 3D segmentation method based on elevation

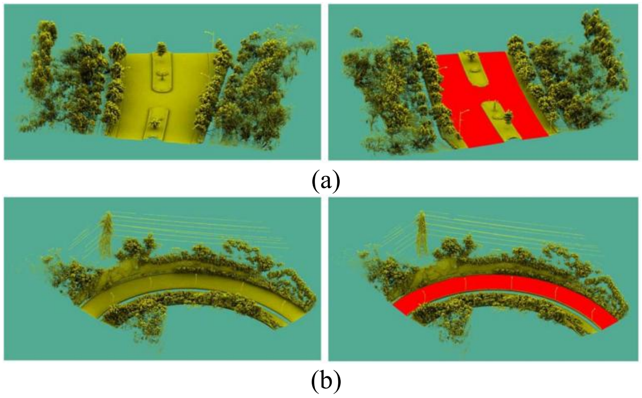

Fig. 1. Two road sections including (left) raw MLS data and (right) extracted road surfaces. (a) Road 1. (b) Road 2 [10].

gradients and 2D image processing methods.

A method using a sigmoidal function to detect curb points from point cloud data was proposed in [4]. The sigmoidal function is applied at locations where middle points of height jumps on a road surface are extracted. The algorithm requires two parameters: one to define the height jump, another to define the slope in the sigmoidal function. The algorithm achieves a completeness rate of 83% and a correctness rate of 90%.

Both large-scale and local-scale of road properties (topology, local shape) are used in [5] to detect curbs semi-automatically. The MLS point clouds are first partitioned based on GPS time. Therefore, between a constant time interval, points are partitioned into cross sections. A moving window is applied in each cross section to detect curbs based on changes in elevation, slope, and point density. This semi-automated algorithm results in 95% high completeness and correctness.

Spacing abnormality between each two ring-shape planar surfaces in the MLS point clouds is used in [6] to detect road curbs. False curb points and occlusion issues are eliminated through a height-value filter and a robust least rimmed squares regression filter. Their algorithm involves four fixed parameters. The result has a 0.52 m lateral positioning error.

Based on the trajectory, a generalized projection based M-estimator is used in [7] to extract road surfaces. Their method is able to deal with roads with varying directions, widths and slopes. However, their method can't deal with the intersection of two roads.

A method was presented in [8] to extract street boundaries and curbs from MLS data. After transforming and rasterizing the data, the edges of the curb are extracted by looking for the points that indicate a slope change.

A novel snake model is applied in [9] to detect road edges using elevation, reflectance, and pulse width derived from MLS data. The advantage of this model is to be able to detect edges from not only urban roads but also rural and national primary road networks. Within a 0.5 m buffer zone, the snake model can achieve 90% completeness and correctness.

An automated curb detection algorithm to generate points that are close to the road surface into pseudo scan-lines was proposed in [10]. Road cross sections can be presented using point-based lines. Curb points are detected based on height jump. By using curb points, a cubic spline interpolation method is applied to form the road edge. The accuracy is within 7-8 cm horizontally and 2 cm vertically (see Fig. 1).

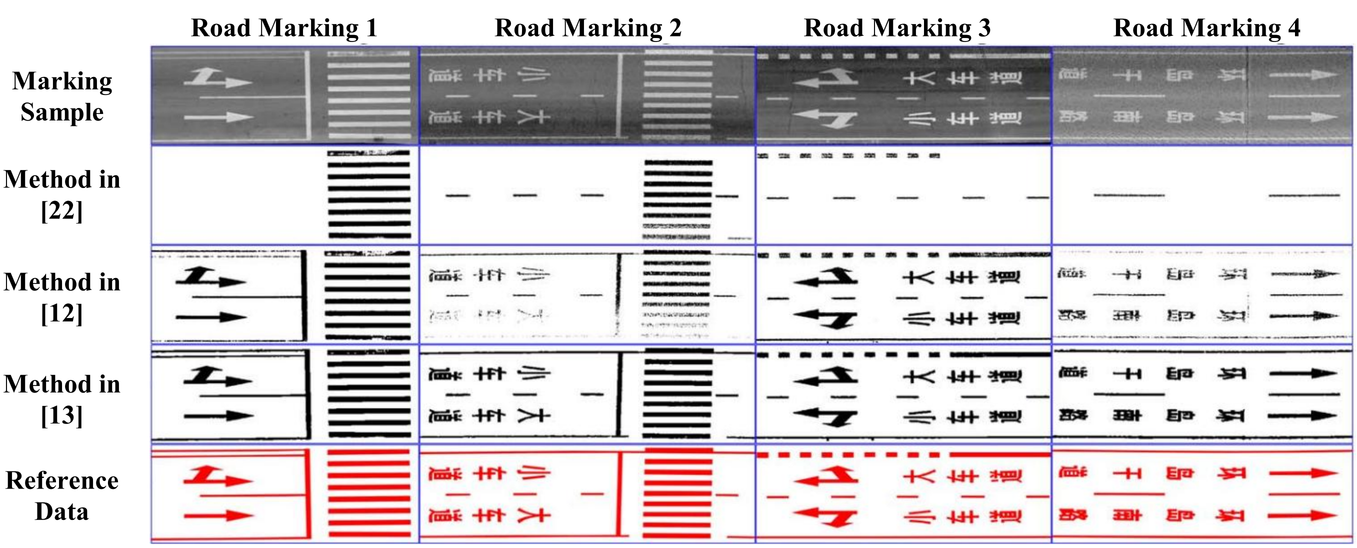

Fig. 2. Extracted pavement markings using different methods [13].

3. EXTRACTION OF ROAD MARKINGS

Besides 3D information, MLS point clouds also provide intensity, pulse width, and range information. Particularly, because road markings often obtain a higher intensity than the road surface, intensity data and range information in MLS point clouds has greatly aided the detection of road markings. By using the retro-reflective property, a series of studies has performed road marking extraction.

Range-dependent thresholding and image post-processing methods are applied in [11] to automatically extract road markings. Markings in circular or irregular shapes acquire lower precision from the extraction result.

In [13], the Inverse Distance Weighting (IDW) interpolation method is applied to derive geo-referenced intensity data from raw road point clouds. By using the IDW interpolation method, points that have lower intensity or are far from the center point have been converted into images associated with lower grey value. Road markings are then refined from the geo-referenced intensity image using morphological operations (see Fig. 2).

Road markings are directly extracted from road surface points through multi-segment thresholding and spatial density filtering in [14]. This method achieves an average completeness, correctness, and F-measure of 0.93, 0.92, and 0.93, respectively.

In [15] point clouds are rasterized into 2D laser cycles. Principal Component Analysis (PCA) is applied to the 2D laser cycles. Hough transform is incorporated into the PCA segmentation result to detect zebra crossing. The performance of the proposed algorithm achieves a completeness of 83%.

4. EXTRACTION OF PAVEMENT CRACKS

Traditionally, images are the preferred source of road crack surveying. However, image quality often depends on weather, traffic, and photogrammetry techniques. Use of MLS data to detect cracks is a relatively new topic. The idea is basically that the 3D information of MLS data will aid in pavement distress analysis. To achieve this idea, a few studies have involved converting 3D point clouds into 2D data and proposing algorithms to extract crack information.

A dynamic optimization-based crack segmentation method is implemented in [16] on high-resolution 3D continuous transverse pavement profiles. The continuous transverse pavement profiles acquired from MLS can aid in detecting road cracks with widths greater than 2 mm. It enables crack detection under low intensity contrast and lighting conditions with a precision score greater than 95%.

Extracting crack skeletons in [17] uses point cloud intensity information to identify pavement cracks that usually exhibit lower intensities compared to their surroundings. Crack candidates are extracted by applying the Otsu thresholding algorithm. Crack skeletons are extracted based on an L1-medial skeleton extraction method. The proposed algorithm was executed very fast and performed very well in extracting 3D crack skeletons.

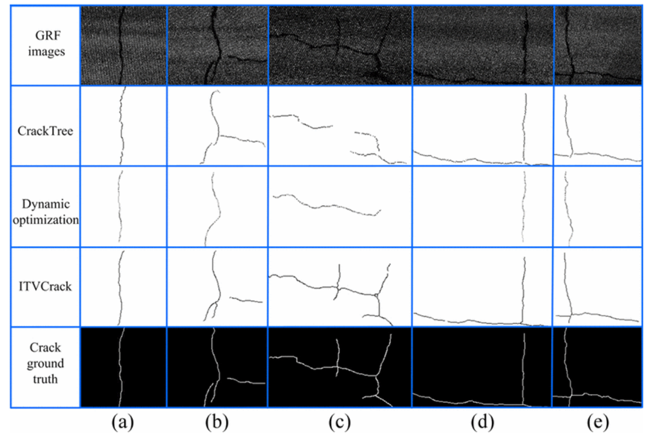

Fig. 3. Comparison of ITVCrack with the other approaches using the GRF images. (a) Crack 1. (b) Crack 2. (c) Crack 3. (d) Crack 4. (e) Crack 5 [18].

An Iterative Tensor Voting algorithm for detecting road Cracks (ITVCrack) from Geo-Referenced Feature (GRF) images was proposed in [18]. The iterative tensor voting based crack detection, which can well detect road cracks with widths larger than 2 cm, achieves a completeness of 96% and correctness of 85%. The computational time, mainly consumed by the iterative tensor voting process, is considerable (see Fig. 3).

5. EXTRACTION OF MANHOLE COVERS

Manholes and sewer wells play a significant role in managing rainfall and other infrastructures. Since most manholes are made of metal materials, their points in MLS data have higher density values against road surfaces. Manhole recognition usually starts with using marked 3D points to extract rectangular or round-shape structures from digital images; then using their high intensity values to extract the targeted manholes.

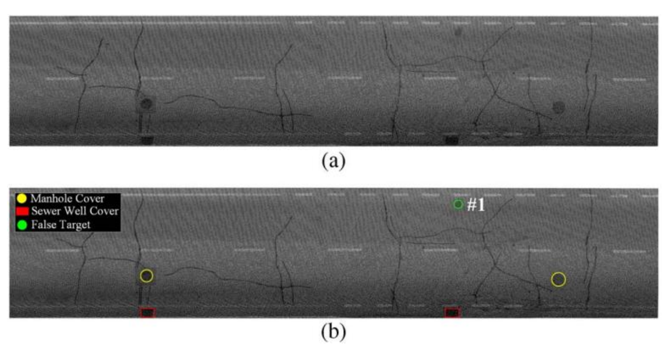

Fig. 4. (a) Geo-referenced intensity image. (b) Detected manhole and sewer well covers [20].

Distance-dependent thresholding, multi-scale tensor voting, distance-based clustering and a morphological operation are used to extract manhole covers in [19] after converting data to geo-referenced feature images. A method using a novel marked point model to detect road manhole and sewer well covers was proposed in [20]. A reversible jump Markov chain Monte Carlo algorithm is applied to stimulate the distribution of manholes. The algorithm achieves very high completeness of 95.16% and correctness of 92.67% (see Fig. 4).

6. CONCLUDING REMARKS

With the blooming of MLS techniques in the last decade, MLS applications have developed rapidly in every part of urban management. Especially, MLS data provides valuable 3D on-road information to transportation agencies. On-road object extraction from MLS point clouds has greatly aided the monitoring of pavement conditions and traffic safety.

In this review, we collected a series of on-road object extraction methods. Most of the reviewed methods achieve desired accuracies. However, the level of automation and computational cost are still in the developmental stage. To extract on-road objects, the tested MLS datasets usually must be pre-processed (such as partition, segmentation, classification, etc.), which indispensably requires artificial interferences and considerable processing time. To the present, there is still no generally accepted automated algorithm for detecting on-road objects. All the methods mentioned above have their own drawbacks to some extent. Thus, further studies still must focus on better automation and reducing computational costs.

REFERENCES

[1] E. Schnebele, B. Tanyu, G. Cervone, and N. Waters, "Review of remote sensing methodologies for pavement management and assessment," *Eur. Transp. Res. Rev.*, vol. 7, no. 2, pp. 1-19, 2015.

[2] K. Williams, M.J. Olsen, G.V. Roe, and C. Glennie, "Synthesis of transportation applications of mobile LiDAR," *Remote Sens.*, vol. 5, no. 9, pp. 4652-4692, 2013.

[3] S. El-Halawany, A. Moussa, D.D. Lichti, and N. El-Sheimy, "Detection of road curb from mobile terrestrial laser scanner point cloud", *Int. Arch. Photogramm., Remote Sens. Spatial Inf. Sci.,* vol. 38, no. Part 5/W12, pp. 109–114, 2011.

[4] L. Zhou, and G. Vosselman, "Mapping curbstones in airborne and mobile laser scanning data," *Int. J. Appl. Earth Obs. Geoinf.*, vol. 18, pp. 293-304, 2012.

[5] B. Yang, L. Fang, and J. Li, "Semi-automated extraction and delineation of 3D roads of street scene from mobile laser scanning point clouds," *ISPRS J. Photogramm. Remote Sens.*, vol. 79, pp. 80-93, 2013.

[6] A.Y. Hata, F.S. Osorio, and D.F. Wolf, "Robust curb detection and vehicle localization in urban environments", in *Proc. IEEE Intell. Veh. Symp.,* Dearborn Michigan USA, pp. 1257-1262, June 8-11, 2014.

[7] H. Wang, C. Wang, Y. Chen, W. Yang, and J. Li, "Extracting road surface from mobile laser scanning point clouds in large scale urban environment", in *IEEE ITSC,* Qingdao China, pp. 2912-2917, October 8-11, 2014.

[8] B. Rodríguez-Cuenca, S. García-Cortés, C. Ordóñez, and M.C. Alonso, "An approach to detect and delineate street curbs from MLS 3D point cloud data," *Autom. Constr.*, vol. 51, pp. 103-112, 2015.

[9] P. Kumar, C.P. McElhinney, P. Lewis, and T. McCarthy, "An automated algorithm for extracting road edges from terrestrial mobile LiDAR data," *ISPRS J. Photogramm. Remote Sens.*, vol. 85, pp. 44-55, 2013.

[10] H. Guan, J. Li, Y. Yu, M. Chapman, and C. Wang, "Automated road information extraction from mobile laser scanning data," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 1, pp. 194-205, 2015.

[11] P. Kumar, C.P. McElhinney, P. Lewis, and T. McCarthy, "Automated road markings extraction from mobile laser scanning data," *Int. J. Appl. Earth Obs. Geoinf.*, vol. 32, pp. 125-137, 2014.

[12] H. Guan, J. Li, Y. Yu, C. Wang, M. Chapman, and B. Yang, "Using mobile laser scanning data for automated extraction of road markings," *ISPRS J. Photogramm. Remote Sens.*, vol. 87, pp. 93-107, 2014.

[13] H. Guan, J. Li, Y. Yu, Z. Ji, and C. Wang, "Using mobile LiDAR data for rapidly updating road markings," *IEEE Trans. Intell. Transp. Syst.*, 2015.

[14] Y. Yu, J. Li, H. Guan, F. Jia, and C. Wang, "Learning hierarchical features for automated extraction of road markings from 3-D mobile LiDAR point clouds," *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 8, no. 2, pp. 709-726, 2015.

[15] B. Riveiro, H. González-Jorge, J. Martínez-Sánchez, L. Díaz-Vilariño, and P. Arias, "Automatic detection of zebra crossings from mobile LiDAR data," *Opt. Laser Technol.*, vol. 70, pp. 63-70, 2015.

[16] Y.-C.J. Tsai, and F. Li, "Critical assessment of detecting asphalt pavement cracks under different lighting and low intensity contrast conditions using emerging 3D laser technology," *J. Transp. Eng.*, vol. 138, no. 5, pp. 649-656, 2012.

[17] Y. Yu, J. Li, H. Guan, and C. Wang, "3D crack skeleton extraction from mobile LiDAR point clouds", in *IEEE IGARSS*, Quebec City Canada, pp. 914-917, July 13-18, 2014.

[18] H. Guan, J. Li, Y. Yu, M. Chapman, H. Wang, C. Wang, and R. Zhai, "Iterative tensor voting for pavement crack extraction using mobile laser scanning data," *IEEE Trans. Geosci. Remote Sens.*, vol. 53, no. 3, pp. 1527-1537, 2015.

[19] H. Guan, Y. Yu, J. Li, P. Liu, H. Zhao, and C. Wang, "Automated extraction of manhole covers using mobile LiDAR data," *Remote Sens. Lett.*, vol. 5, no. 12, pp. 1042-1050, 2014.

[20] Y. Yu, J. Li, H. Guan, C. Wang, and J. Yu, "Automated detection of road manhole and sewer well covers from mobile LiDAR point clouds," *IEEE Geosci. Remote Sens. Lett.*, vol. 11, no. 9, pp. 1549-1553, 2014.

[21] B. Yang, L. Fang, Q. Li, and J. Li, "Automated extraction of road markings from mobile LiDAR point clouds," *Photogramm. Eng. Remote Sens.*, vol. 78, no. 4, pp. 331–338, 2012.