3D point-based high-definition road maps for autonomous driving

Jonathan LI and Lingfei MA, Canada, Yiping CHEN* and Cheng WANG, China

Key words: Cartography, Laser scanning, Photogrammetry, HD Map, Point Cloud

SUMMARY

The research and development for autonomous vehicles have attracted more than half of today's venture capital investment worldwide. Multiple sensors installed on vehicles are playing a critical role for vehicle navigation. However, on-board sensors have limitations such as short detection ranges, especially in an urban canyon and GPS-denied indoor environment. As such, 3D high-definition road maps are urgently required for autonomous driving. Mobile laser scanners (MLS) onboard a minivan have been proved the feasible technology for rapid collection of citywide road network data to create 3D road maps. However, unstructured MLS point clouds with its large volume, varied density, and lack of surface texture, make the automation in point-based road mapping extremely challenging. This paper presents the machine learning based approaches to automated detection and extraction of road edge line, lane lines and driving lines from 3D point clouds. The results obtained demonstrate that the developed approaches are very promising. The progress in intelligent processing of point clouds also shows mobile laser scanners' advantages over its counterpart digital cameras. The paper also presents preliminary results obtained by a SLAM-based laser scanning backpack and a low-cost mobile system for supporting automated parking in the GPS-denied indoor environment.

3D point-based high-definition road maps for autonomous driving

Jonathan LI and Lingfei MA, Canada, Yiping CHEN* and Cheng WANG, China

1. INTRODUCTION

Recently, the design and development of autonomous vehicles with intelligent and coordinated action capabilities to achieve self-driving without human interactions, has been the object of considerable interest in the artificial intelligence and automotive engineering communities. An autonomous vehicle has the capability to determine the best navigation routes, drive itself on the most challenging road networks, and avoid collisions with fixed or moving road users (e.g., pedestrians, cyclists and cars) without direct human operations. Consequently, many worldwide prominent automotive manufacturers (e.g., General Motors, BMW, Mercedes-Benz, Audi, Fiat Chrysler, Toyota, and Ford) and communication technology (ICT) companies (e.g., Google, Uber, Apple, Tesla, Baidu and Nvidia), are investing heavily, adjusting their development strategies, and indicating their ambitions to participate in the emerging market of self-driving vehicles.

Typically, autonomous vehicles are equipped with several data acquisition devices that work in combination with each other to achieve highly autonomous driving. Radar sensors, video cameras and LiDAR sensors mounted on the vehicle are able to detect road edges and identify driving lines by emitting continuous laser pulses and receiving the reflected signals. However, autonomous vehicles cannot achieve highly autonomous driving function in rural road environments without road markings or the curbs of the roadways. Therefore, autonomous vehicles depend on three-dimensional (3D) high-definition roadmaps to support precise vehicle positioning and route navigating services for all road environments (Katrakazas et al., 2015[1]).

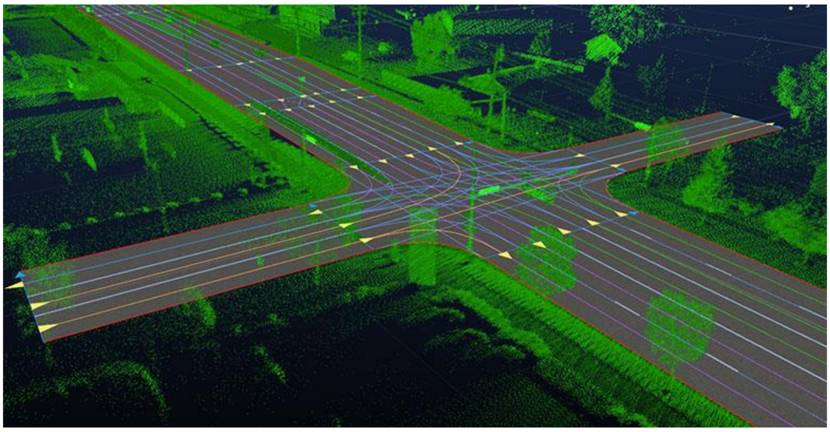


Figure 1. The HD Live Map from point clouds data.

Compared to the conventional road maps, the 3D high-definition roadmaps are developed for more precise traffic navigation with high accuracy and detailed road network information (e.g., lanes, road edges, centrelines, and restrictions). Mobile Laser Scanning (MLS) technique is applied to acquire high-resolution topographic data and construct 3D road models with highly sensitive information about road infrastructures.

This paper will focus on elaborating reasonable rationales and proposing semi-automatic algorithms to generate reliable and effective driving lines using MLS point clouds at horizontally curved road sections.We illustract the driving lines results from a SLAM-based laser scanning backpack. Based on geomatics, computer vision, mobile mapping technologies and road design regulations, the proposed method in this paper is to enable a prospective application of MLS data for making 3D HD maps to support autonomous vehicles.

2. RELATED WORK

Automated detection and extraction of driving lines are basic research work for HD maps. A variety of methods and algorithms were developed to detect and extract road surface from MLS data. Typically, these methods are mainly classified into three categories based on: 1) road geometric shape; 2) MLS data characteristics and road properties; and 3) 2D or 3D geometric feature filtering. Several model fitting methods were employed for direct extraction of planar road surfaces (Guan et al., 2017[2], Cheng et al., 2017[3]). According to the working principles of a MLS system, point density is negatively correlated with the increase of scanning range from the vehicle trajectory. Zai et al. (2017[4]) presented a 3D road edge extraction approach based on varied densities of MLS point clouds. Yang et al. 2012 [5]) proposed a method to separate road and off-road points towards road marking detection based on georefereced feature imagery coverted from MLS point clouds by analyzing intensity of road points. Wang et al. (2012[6]) implemented a method to detected road edges and extracted road surfaces by taking height difference values, altitude mean values and altitude variances into consideration. Riveiro et al. (2015[7]) performed a road segmentation method using a curvature analysis directly interpreted from MLS data.

Multiscale threshold segmentation, Hough Transform, morphology and Multi-scale Tensor Voting (MSTV) were applied with regard to semantic information of road markings, e.g. lane lines (Riveiro et al., 2015[7]; Guan et al., 2015[8];). Meanwhile, many studies focused on extracting road markings from 3D point clouds directly rather than from 2D geo-referenced feature images. Accordingly, Yu et al. (2015[9]) implemented the road marking extraction directly from 3D point clouds and classified road markings into edge lines, stop lines, zebra crossing lines, arrow markings, rectangular markings and centerlines.

Horizontal curves have been regarded as an important element in the process of urban road network design and construction. McDonald (2004[10]) indicated that the accident frequency could increase by 34% for per sharp curve per km. Moreover, drivers' behaviours including misperceptions of speed and poor visibility at horizontal curves, can lead to the increase of potential risks of traffic accidents. Thus, detecting traffic health condition especially at horizontally curved road sections and determining road horizontal parameters (e.g., curvature) are significant for autonomous vehicles to determine reliable driving lines and prevent collisions (Charlton, 2007[11]). Many studies have been performed to extract geometric parameters at horizontally curved road sections by using MLS systems. For instance, Karamanou et al. (2009[12]) developed a software for precise estimations of road horizontal geometric features using a suitably equipped vehicle moving along the road in a two-way trip. Moreover, based on dynamic measurements of GNSS, Di Mascio et al. (2012[13]) implemented a procedure to define the road geometry of horizontal elements. Other studies focused on automated extraction of off-road objects, such as traffic signs (Wen et al. 2016 [14]; Yu et al. 2016 [15]).

The purpose of this paper is to develop semi-automated algorithms for the detection and extraction of road markings particularly for lane lines, centrelines and edge lines at the horizontally curved road sections. Furthermore, to generate horizontally curved driving lines based on high-density MLS point clouds can support the development of autonomous vehicles.

3. METHOD

This section details the proposed methodology of semi-automated generation of horizontally curved driving lines. Firstly, we present a step-wise methodology, including curb-based road surface extraction in subsection 3.1, multiscale thresholds-based road marking extraction in subsection 3.2, and best-fitting curve-based driving line generation at horizontal curves in subsection 3.3.

3.1 Road edge extraction

The MLS point clouds contain a large number of highly dense and unevenly distributed point clouds, including buildings, trees, traffic infrastructures, pedestrians and other ground points. In order to eliminate the disturbance of non-ground laser point clouds and improve computational efficiency for road marking extraction, the curb-based road surface extraction algorithms is firstly implemented by using the vehicle's trajectory data. Firstly, point clouds profiling. Depending on the vehicle trajectory data, the raw test datasets are partitioned into a sequence of point cloud data blocks, in each of which a corresponding profile is sectioned with a certain width accordingly. Secondly, pseudo scan-line generation. The point clouds contained in the profile are projected onto the plane perpendicular to the direction in which the vehicle is forward. Each profile is then gridded to generate a pseudo scan-line and a principal point is determined within a grid cell accordingly. Third, road curb detection. Based on both elevation and slope differences, road curbs are detected and extracted from each pseudo scan-line. Based on the final report of the Code for Design of Urban Road Engineering submitted to PRC Minister of Construction in 2012, majority of curb heights within the study area are ranging from 8 cm to 30 cm. The last step is road edge fitting. Finally, a cubic B-Spline interpolation algorithm is employed to fit the curb points derived from all pseudo scan-lines into two smooth road edges. All point clouds located between two smooth edge lines are regarded as road surface points. Thus, the point clouds pertaining to pavements are extracted from the raw MLS data.

3.2 Multiscale thresholds-based lane lines extraction

The proposed curb-based algorithms have been described in Section 3.1 for road edge detection and extraction using MLS data. In order to segment lane lines completely and effectively, the labelled road surface points are firstly interpolated to generate a 2D GRF image (e.g., intensity imagery). Then, to eliminate the influence of noisy points and improve road marking completeness, a multi-threshold segmentation approach is performed on the produced GRF image to identify and extract lane lines using a morphological operation. Moreover, experimental results and discussion are detailed in Section 4. This road marking extraction method can be described as a step-wise procedure. It generation of geo-referenced intensity imagery. Road surface points are first extracted from raw MLS data by utilizing the proposed curb-based extraction algorithms, these road points are then interpolated into geo-referenced intensity imagery based on the IDW method in combination with intensity information and local-global elevation data. Then, multi-threshold extraction. Then, based on the generated intensity imagery, the multi-threshold extraction algorithms are employed to extract lane lines. Finally, a statistical outlier removal filter is carried out in order to eliminate noises and enhance lane lines completeness.

3.3 Generation of Horizontally Curved Driving Lines

In order to generate driving lines at horizontal curves successfully, the sparse and unorganized road marking points are first clustered into topological and semantic objects using the conditional Euclidean clustering method. Then, to determine the best matching functions and perform curve-fitting for curved lane lines, a least-squares curve-fitting method is applied on the generated clustered points by minimizing the sum of the squares of the residuals. According to the distances between a certain point and its nearest points, a conditional Euclidean clustering method is employed to segment the 3D discrete road marking points into a series of organized clusters. Nonlinear least-squares curve fitting. A nonlinear least-squares curve fitting algorithm is carried out to determine the best-fitting horizontal curves. The driving lines are determined based on the mathematical functions of the generated best-fitting curves and the road design and construction standards.

4. EXPERIMENT

This section presents and discusses the experimental results of driving line generation using MLS point clouds at horizontally curved road sections. Firstly, we describe the MLS test datasets and reference data used in this study. Secondly, the experimental results obtained using the proposed step-wise methods are demonstrated and discussed. Finally, the results of accuracy assessment and comparative study are presented in order to evaluate the performance of the proposed methods in reliability and efficiency.The MLS point cloud datasets used in this study were collected by a research team using a RIEGL VMX-450 system mounted on a Buick GL8 minivan. The VMX-450 system cosists of two fully calibrated RIEGL VQ-450 laser scanners, four RIGEL VMX-450-CS6 digital cameras with pixel array of 2452H by 2056V, and one integrated Applanix POS LV 520 processing system with one GNSS antenna, one IMU, one DMI and one POS computing system (PCS). Based on a point-of-sale synthetic computer system, main components are assembled within a case and mounted on the roof of a motorized vehicle. Six test datasets were selected from the point clouds obtained by the VMX-450 system.

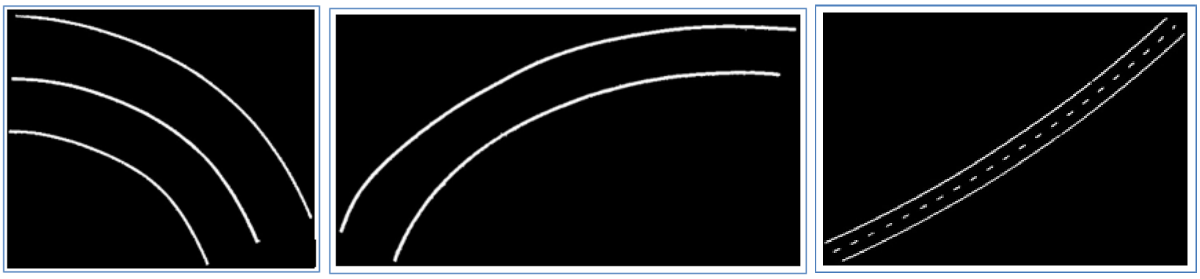
4.1 Experiment results of the proposed method

To validate the performance and reliability of the proposed road marking extraction algorithms, an accuracy assessment is performed based on the manually created reference data.

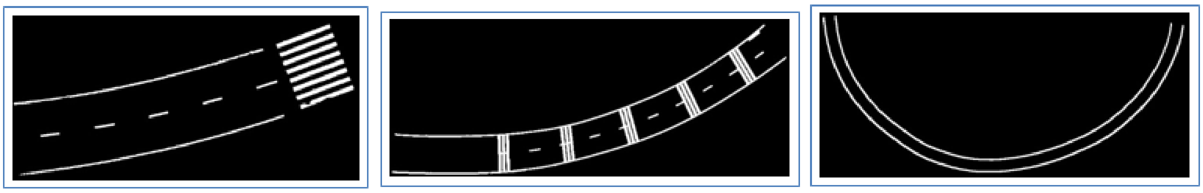
Table 1 Confusion matrix of binary classification

Class \ Classified	Positive	Negative
Positive	*TP*	*FN*
Negative	*FP*	*TN*

Table 1 presents a confusion matrix for the binary classification, where *TP* and *TN* represent a true positive and negative classification while *FP* and *FN* indicate a false positive and negative classification, respectively. In this paper, the target class (positive class) is the extracted road marking class, and the road surface class is regarded as the negative class.



(a) (b) (c)



(d) (e) (f)

Figure 2. Extracted road markings after noise removal from six test datasets I to VI.

In our study, the accuracy assessment mechanism of road marking extraction is based on Recall, Precision and F1-score (Powers, 2007[16]). The recall indicates how complete the extracted road markings are, while precision describes what percentage of the extracted road markings are valid. In addition, F1-score represents an overall score with the integration between recall and precision.

Figure 3. Road lines results obtained by a SLAM-based laser scanning backpack.

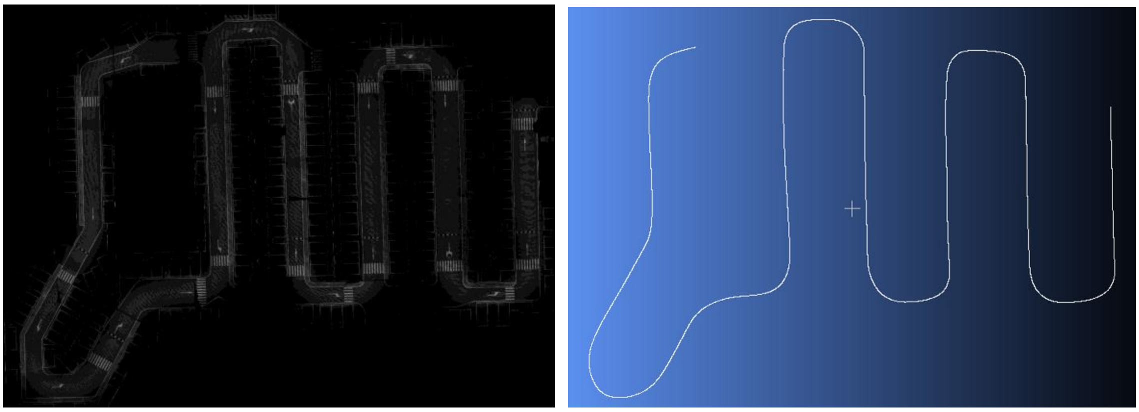


Figure 4. Driving lines from SLAM-based laser scanning backpack.

Table 2 Accuracy assesement of road marking extraction.

Dataset / Performance (%)	1	2	3	4	5	6	Average
Recall	90.06	93.73	90.42	88.02	92.71	90.42	90.89
Precision	92.53	95.04	93.05	89.59	94.97	93.05	93.04
F1-score	91.28	94.38	91.72	88.80	93.83	91.72	91.95

In the GNSS-denied environments such as indoor parking lots, we have developed a laser scanning backpack with two Velodyne PUCK laser scanner based on the simultanous localization and mapping (SLAM) algorithm (Gong et al. 2017 [17]). The experimental results of our self-developed backpack laser scanning system are shown in Figures 3 and 4. As illustrastred in Table 2, the quantitative assessments were conducted based on the recall, precision and F1-score. As a result, the proposed road marking extraction and noise removal algorithms are capable of obtaining 90.89% in recall, 93.04% in precision and 91.95% in F1-score, respectively. The value of precision is larger than that of recall for each sample, which demonstrates that centain road marking pixels were misclassified as road surfaces. Additionally, the size of manually labelled reference data are larger than the road markings due to the decay of them. Thus, the overall performance of the proposed road marking extraction algorithms is underestimated in the final results.

4.2 Comparative results

Furthermore, a comparative study was carried out concentrating on the extracted road marking results by using the proposed algorithms and other methods, i.e. Chen et al. (2009[6]) and Yu et al. (2015[9]). MLS point clouds were used directly in the process of road marking extraction in both Chen's [6] and Yu's [9] methods. Chen's [6] method mainly focuses on the lane marking extraction along the moving direction of the vehicle, resulting in limitations at the stage of complex and semantic road marking extraction (e.g., arrows, words and curved road markings). Meanwhile, based on deep learning and PCA methods, Yu's [9] approach can be applied in the extraction of any types of road markings but it has limitations in the process of curved road marking extraction and also it requires rich prior knowledge.

Table 3 Comparison of the three methods in quantitative evaluation.

Test Datasets	I			IV			V		
Methods	Chen et al., 2009	Yu et al., 2015	Our method	Chen et al., 2009	Yu et al., 2015	Our method	Chen et al., 2009	Yu et al., 2015	Our method
Recall (%)	71.85	81.83	90.06	73.44	75.98	89.02	82.66	84.39	91.73
Precision (%)	90.83	91.43	92.55	92.78	91.55	89.78	90.95	91.42	93.99
F1-score (%)	81.93	88.92	91.29	83.11	83.37	88.91	86.71	87.32	93.70

The overall performance of the proposed method and other three methods are evaluated based on the quantitative assessment (i.e., recall, precision and F1-score). Table 3 indicates that the proposed method can achieve a better performance than both Chen's [6] and Yu's [9] methods in terms of both recall and precision. Moreover, it demonstrates the revised multi-thresholds extraction method in this paper can effectively extract curved road markings (e.g., centrelines, edge lines and lane lines) at horizontally curved road sections.

5. CONCLUDING REMARKS

In this paper, road edge points are extracted by first from raw MLS data to enhance computational efficiency using the curb-based extraction algorithms. Subsequently, curved road markings (e.g., centrelines, lane lines and edge lines) are extracted from the generated intensity imagery based on a multi-threshold extraction method, and discrete noises are filtered out using the SOR filter. The nonlinear least-squares curve fitting algorithm is employed to determine the best-fitting mathematical functions of curved road markings. Finally, the candidate points of driving lines can be calculated based on both road design and construction standards and the generated best-fitting functions of curved road markings.

In this study, six datasets are used to evaluate the feasibility and validity of the proposed methods. Based on the quantitative assessment and comparative study, the proposed road marking extraction algorithms are capable of achieving 90.89% in recall, 93.04% in precision and 91.95% in F1-score, respectively.

The overall performance indicates that majority of proposed algorithms in the process of driving line generation are highly efficient and time-saving. This paper concludes that the proposed methodology is capable of efficient generation of the driving lines at horizontally curved road sections from MLS data to provide highly accurate localization services. It also provides a reliable solution to overcome the huge challenges for worldwide automotive manufacturers, technology corporations and mapping companies, including BMW, Tesla, Google, HERE and TomTom, who are committed to the generation of 3D high-definition roadmaps and promotion of autonomous vehicles. This paper was suppored in part by the NSFC grant no. 61601392.

REFERENCES

[1] Katrakazas, C., Quddus, M., & Chen, W. H., 2015. Real-time motion planning methods for autonomous on-road driving: State-of-the-art and future research directions. *Transportation Research Part C*,vol 60, pp:416-442.

[2] Guan, H., Li, J., Cao, S., & Yu, Y., 2016. Use of mobile LiDAR in road information inventory: a review, *International Journal of Image and Data Fusion*, 7(3): 219-242.

[3] Cheng, M., Zhang, H., Wang, W., & Li, J., 2017. Extraction and classification of road markings using mobile laser scanning point clouds, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 10(3), 1182-1196.

[4] Zai, D., Li, J., Guo, Y., Cheng, M., Lin, Y., Luo, H., & Wang, C., 2017. 3D road boundary extraction from mobile laser scanning data via supervoxels and graph cuts, *IEEE Transactions on Intelligent Transportation Systems*, doi:10.1109/TITS.2017.2701403.

[5] Yang, B., Fang, L., Li, Q., Li, J., 2012. Automated extraction of road markings from mobile LiDAR point clouds. Photogrammetric Engineering & Remote Sensing, vol. 78, no. 4, pp. 331-338.

[6] Chen, X., Kohlmeyer, B., Stroila, M., Alwar, N., Wang, R., & Bach, J., 2009. Next generation map making: Geo-referenced ground-level LiDAR point clouds for automatic retro-reflective road feature extraction. *The Association for Computing Machinery*, pp. 488-491.

[7] Riveiro, B., González-Jorge, H., Martínez-Sánchez, J., Díaz-Vilariño, L., & Arias, P., 2015. Automatic detection of zebra crossings from mobile LiDAR data. *Optics & Laser Technology*, vol. 70, pp. 63-70.

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

[9] Yu, Y., Li, J., Guan, H., Jia, F., & Wang, C., 2015. Learning hierarchical features for automated extraction of road markings from 3-D mobile LiDAR point clouds. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 8, no. 2, pp .709-726.

[10] McDonald, N., 2004. Look and learn: capitalising on individual responsibility in speed management. *In: Proceedings of the 2004 Australian Institute of Traffic Planning and Management National Conference, Australian Institute of Traffic Planning and Management*, pp. 71–83.

[11] Charlton, S. G., 2007. The role of attention in horizontal curves: A comparison of advance warning, delineation, and road marking treatments. *Accident Analysis & Prevention*, vol. 39, no. 5, pp. 873-885.

[12] Karamanou, A., Papazissi, K., Paradissis, D., & Psarianos, B., 2009. Precise estimation of road horizontal and vertical geometric features using mobile mapping techniques. *Boletim de Ciências Geodésicas*, vol. 15, no. 5.

[13] Di Mascio, P., Di Vito, M., Loprencipe, G., & Ragnoli, A., 2012. Procedure to determine the geometry of road alignment using GPS data. *Procedia-Social and Behavioral Sciences*, vol. 53, pp. 1202-1215.

[14] Wen, C., Li, J., Luo, H., Yu, Y., Cai, Z., Wang, H., & Wang, C,, 2016. Spatial-related traffic sign inspection for inventory purposes using mobile laser scanning data. IEEE Transactions on Intelligent Transportation Systems, vol. 17, no. 1, pp. 27-37.

[15] Yu, Y., Li, J., Wen, C., Guan, H., Luo, H., & Wang, C., 2016. Bag-of-visual-phrases and hierarchical deep models for traffic sign detection and recognition in mobile laser scanning data. ISPRS Journal of Photogrammetry and Remote Sensing, vol. 113, pp. 106–123.

[16] Powers, D.M.W., 2007. Evaluation: From precision, recall and f-factor to ROC, informedness, markedness & correlation, Flinders University, Adelaide, Australia, Technical Report SIE-07-001, pp. 1-24, https://csem.flinders.edu.au/research/techreps/SIE07001.pdf, online access 18 February 2018.

[17] Gong, Z., Wen, C., Wang, C., & Li, J., 2017. A target-free automatic self-calibration approach for multi-beam laser scanners, *IEEE Transactions on Instrumentation and Measurement*, vol. 67, no. 1, pp. 238-240.