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Dinir Imameev, Aufar Zakiev, Tatyana Tsoy, Yang Bai, Mikhail Svinin, Evgeni Magid, "LIDAR-based parking spot search algorithm," Proc. SPIE 11605, Thirteenth International Conference on Machine Vision, 1160502 (4 January 2021); doi: 10.1117/12.2587070

Event: Thirteenth International Conference on Machine Vision, 2020, Rome, Italy

LIDAR-based Parking Spot Search Algorithm

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ABSTRACT

Autonomous driving considers issues related to a car driving in different real world situations. This work addresses a parking task and describes a new LIDAR-based parking spot search algorithm. The proposed approach was successfully validated in virtual experiments within the Gazebo simulator in a parking area with a perpendicular parking setup. HDBScan, OPTICS, and Gaussian Mixture clustering methods were compared for LIDAR data clustering in the parking spot search task, and the HDBScan clustering demonstrated best prediction and performance results.

Keywords: Clustering algorithms, LIDAR, laser range finder, LRF, parking, autonomous vehicle, robot operating system, ROS.

1. INTRODUCTION

Automation and robotic application within Industry 4.0 concept are key aspects of the new industrial revolution [1]. Autonomous vehicles are an integral part of the revolution because of their increasing efficiency in the area of logistics and consumer market [2, 3]. An autonomous vehicle development considers a set of tasks required for a vehicle driving without a human intervention [4]. This includes a complete autonomous driving itself and multiple smaller-scale tasks related to assisting a driver, e.g., a highway driving, a parallel parking, and a garage parking [5]. Fully-functional assistant systems require complex methods of an obstacle detection [6], [7], an open-loop motion planning [8] and a closed-loop control [9]. This work considers only a problem of parking spot search for a perpendicular parking setup. Such problem statement allows integrating the developed algorithm into an arbitrary navigation stack [10].

Parking is a hard problem for both amateur drivers and expert ones. In general, the parking process includes search for a free parking spot and a car motion to the selected spot. The motion could become risky due to mistakes in the parking spot size estimation and car maneuvering process. Therefore, modern auto manufacturers develop their own parking assistance solutions. For example, Toyota Prius offers Intelligent Parking Assist [11], Ford presents Active Park Assist [12], BMW [13] and Mercedes [14] have their own commercial solutions. However, to the best of our knowledge, no parking spot search algorithm is integrated into available on the market parking assistants and they require a human driver to find an appropriate parking spot and drive a car as close as possible to the selected spot. Our solution allows a car to automatically find a parking spot and navigate the car to the selected spot.

This work proposes a new parking spot search algorithm, which processes only LIDAR data. The algorithm uses a clustering method to evaluate LIDAR-based point sets that represent vehicles within a parking area with a perpendicular parking setup. Cluster analysis identifies free parking spots and provides their coordinates for further navigation.

The proposed algorithm was applied for Avrora Unior robot (Fig. 1), which had been developed by Russian company Avrora Robotics for research and education purposes, including autonomous driving. Avrora Unior is equipped with four ultrasonic parking sensors in the front and four in the rear of the vehicle. Its Microsoft Kinect sensor and Hokuyo laser rangefinder URG-04LX-UG01 on the top of the robot both face a forward motion direction. The robot has a width of 70cm, a length of 112cm and a height of 57 cm. The Avrora Unior's chassis has two rear driven wheels and two front steering wheels, which form Ackermann steering system. Three popular data clustering methods (HDBScan, OPTICS, and Gaussian Mixture) were compared for LIDAR data clustering in the parking spot search task.

Thirteenth International Conference on Machine Vision, edited by Wolfgang Osten, Dmitry Nikolaev, Jianhong Zhou
Proc. of SPIE Vol. 11605, 1160502 · © 2021 SPIE · CCC code: 0277-786X/21/$21 · doi: 10.1117/12.2587070

Figure 1. Avrora Unior robot in the Laboratory of Intelligent Robotic Systems (LIRS, KFU).

The main contribution of this work is the parking spot search algorithm, the three clustering methods comparison for the parking spot search task in a virtual environment of the Gazebo simulator and the algorithm validation in the robot operating system (ROS). The comparison analysis demonstrated that HDBScan clustering had the best prediction and performance results relatively to its counterparts.

2. RELATED WORK

A parking spot search requires data about a surrounding environment. A type of onboard sensors defines the parking spot search algorithm structure and working process. Typically, a video stream from a camera or range readings from a laser range finder (LRF) serve as main sources of environment data for a mobile robot or an autonomous vehicle [15].

Considering a video stream, an omni-camera or a sensor fusion approach allow achieving 360° scope of view. In such case, a parking spot detection is based on key road elements extraction, e.g., parking spot boundaries [16, 17]. For our case, solutions with a video stream processing were rejected since they require installing additional onboard cameras for Avrora Unior and are featured with a strong dependency on road markings quality. Even though a parking spot detection could be implemented via image classification based on neural networks and key elements detection in road markings, often parking areas spots do not have any explicit road markings.

In LRF-based approaches, a sensing range varies significantly depending on LRF technical parameters [18, 19, 20]. A 2D [21] or a 3D [22] LRF could be applied in the proposed approach. We used 2D laser data processing of Hokuyo URG-04LX-UG01 sensor, which is installed on the top of Avrora Unior. For object detection and classification based on 2D LRF data, we applied a clustering technique[23, 24]. Yet, while the existing solutions do not cover parking problem, our approach extended this clustering technique for a parking spot evaluation.

3. SIMULATION SETUP

ROS framework was used together with the Gazebo simulator in order to construct a complex virtual testing environment and evaluate our algorithm behavior [25]. Currently, Avrora Unior model [26] has a work-in-progress status and its navigation stack is not fully implemented yet. For this reason, the proposed algorithm was validated with a fully integrated into ROS Turtlebot3 Burger model while targeting for its further transfer and usage with Avrora Unior. To keep consistency between Turtlebot and Avrora Unior sensory perception, the Turtlebot model was modified in a such way that the LRF location (position values *X=0; Y=0; Z=0.565*) and orientation (orientation values *R=0; P=0.261799; Y=0*) at the Turtlebot would exactly correspond to those of the Avrora Unior. Next, the LRF's properties were modified to correspond to Hokuyo URG-04LX sensor capabilities, i.e., 240° scanning angle and range of up to 5.6 m. The Avrora Unior and Turtlebot models are shown in Fig.2.

An environment that mimics a real parking area was created in the Gazebo simulation. It includes pickup cars and a golf cart [27] located orthogonally the robot motion direction. Two available (free) parking spots are located between the wall and the vehicles and another two are located between vehicles, on the left and the right sides of the lane (Fig.3).

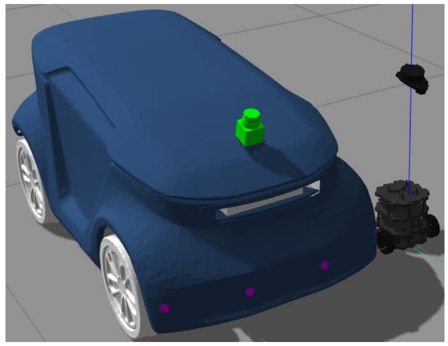


Figure 2. Avrora Unior (left) and modified Turtle-bot3_burger (right); the two LRFs have the same position and orientation.

Figure 3. Parking spots marked in the simulation.

4. PARKING SPOT SEARCH ALGORITHM

The developed algorithm is designed for parking areas with a perpendicular car parking spots setup. The virtual experiment flow imitates a car parking process in a parking area with a car moving on a lane between spots and searching for an available spot. The following steps are performed:

1. A robot spawns at a parking area boundary
2. The robot moves towards the other boundary of the parking area along a lane
3. The robot detects an available parking spot
4. The robot moves to the detected parking spot

The entire process is visualized in RViZ demonstrating LRF readings, a maximum scanning range and detected parking spots. The expected result is a successful detection and a visualization of all available parking spots when the robot passes the corresponding free spots.

The parking spot search is based on LIDAR sensory data, which are preprocessed and analyzed in order to find a free parking spot. The onboard LRF is tilted in the forward motion direction with a pitch angle of 0.261799 rad. Thus, part of the LRF rays intersect a road surface in front of the robot. The preprocessing stage includes filtering of obtained LRF readings: all laser rays intersecting the road surface are filtered out to avoid processing the surface as an obstacle (*scan_side_points_tf* node in the Fig. 4). Next, *scan_points_tf* node transforms filtered LRF readings into Cartesian coordinates to prepare them for a further clustering process. Laser scan points require clustering to identify distinct cars' outlines. The *scanner_node* analyzes a space between distinct outlines and, if the space is sufficient for the robot, returns the detected parking spot position.

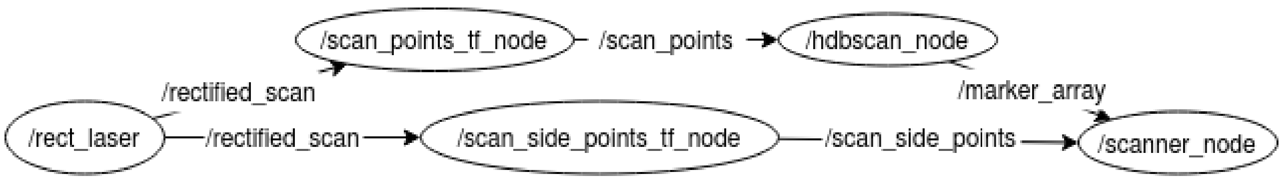
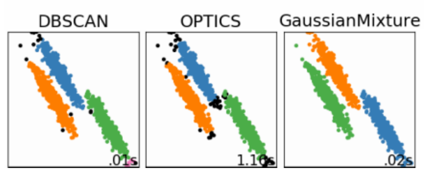


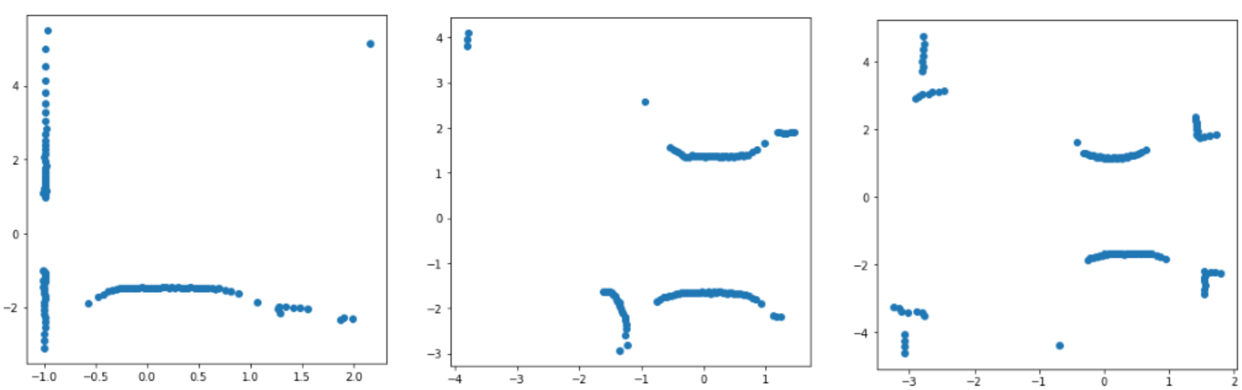
Figure 4. Node architecture.

5. CLUSTERING ALGORITHMS COMPARISON

A clustering task has various approaches that should be respectively applied in different situations. HDBScan [28], OPTICS [29], Gaussian Mixture [30] approaches were selected as candidates for LIDAR data clustering task since they demonstrate best results on a dataset, which consists of straight lines representing parts of vehicle silhouettes retrieved by the LRF (Fig.5a). To compare their performance in LIDAR data clustering task we created a special dataset that consisted of laser scanning data collected in the virtual parking area and considered various ways of car outlines (Fig.5b). Since the dataset was collected using a virtual sensor, it implicitly counted for sensory limitations, e.g., points density decreases as a distance from the LIDAR increased.



(a) Clustering algorithms. The figure is borrowed fromscikit-learn.org and cropped



(b) Sets No1,No3 and No7 from the dataset.

Figure 5. Clustering setup.

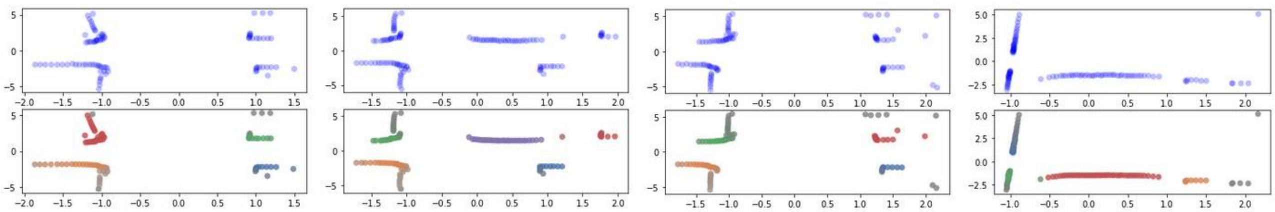
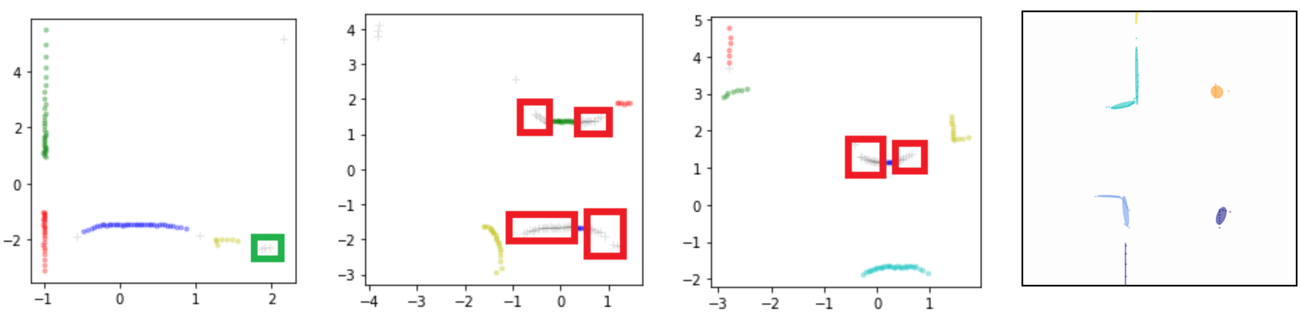


Figure 6. HDBScan test results.

HDBScan is a modified DBScan [31] algorithm implementation with an automatic choice of *threshold_distance*. The results of HDBScan algorithm are presented in Fig.6. The algorithm spent 2-9 ms on data clustering and automatically removed noise points and points with low probability of belonging to any class.

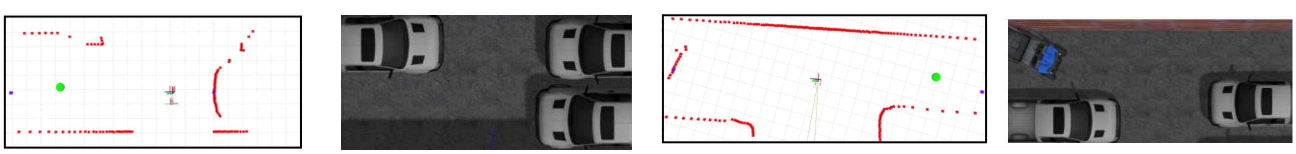


(a) OPTICS, set №1 (b) OPTICS, set №3 (c) OPTICS, set №7 (d) Gaussian Mixture, set №9

Figure 7. OPTICS and Gaussian Mixture testing results. Noise removing overuse in OPTICS algorithm is highlighted by red rectangles.

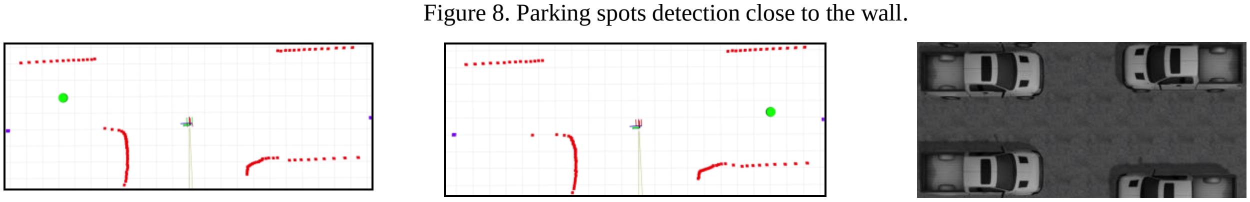
OPTICS is a clustering algorithm with an automatic noise removal (shown as grey points in Fig. 7a). However, it requires x_i parameter adjusting that leads to different clustering quality for different point sets (Fig. 7a-c). The algorithm testing results are shown in Fig. 7a-c.

Gaussian Mixture algorithm demonstrated poor results in our task since it uses ellipse detection for clusters that is inefficient for a vehicle outline detection. For example, it could divide a cluster, which other clustering algorithms identify as a single outline (Fig.7d).



(a) Parking spot position in Rviz (green marker) (b) Parking spot in Gazebo (on the left side) (c) Parking spot position in Rviz (green marker) (d) Parking spot in Gazebo (on the right side)

Figure 8. Parking spots detection close to the wall.



(a) Left parking spot position in Rviz (b) Right parking spot position in Rviz (c) Two parking spots (on the left and right sides) in Gazebo

Figure 9. Parking spot between vehicles.

Finally, HDBScan clustering method was selected for the proposed parking spot search algorithm due to its best prediction and performance results relatively to its counterparts.

6. RESULTS

The algorithm successfully detected all free parking spots in the parking area. In Fig. 8, 9 the detected available parking spots are marked as green dot in the center of each spot, red dots represent LRF readings and blue points show a maximal length of a free parking spot. The algorithm design allows simultaneous processing of right and left parking rows with each row being processed in a separate thread. In the virtual experiments the algorithm successfully found spots between vehicles as well as between vehicles and the parking area boundaries. Moreover, data processing approach doesn't depend on a type of a vehicle or its silhouette, and there are no restrictions on a parking area length.

7. CONCLUSIONS

This paper addressed an autonomous parking task for car-like robots and described a new LIDAR-based parking spot search algorithm. The algorithm used only LIDAR sensory data, which were preprocessed and clustered in order to identify distinct vehicles in a parking area. The algorithm is suitable for a robot with a tilted relatively to the horizon LIDAR sensor. The proposed approach was successfully validated in virtual experiments for *Turtlebot3_burger* wheeled mobile robot within the Gazebo simulator in a parking area with a perpendicular parking setup. HDBScan, OPTICS, and Gaussian Mixture clustering methods were compared for LIDAR data clustering in the parking spot search task, and the HDBScan clustering demonstrated best prediction and performance results. As a part of the ongoing work, the algorithm will be validated for Avrora Unior car-like robot both in the Gazebo simulator and in real world environment.

ACKNOWLEDGEMENTS

This work was supported by the Russian Foundation for Basic Research (RFBR), project ID 19-58-70002.

REFERENCES

[1] H. Lasi, P. Fettke, H.-G. Kemper, T. Feld, and M. Hoffmann, ‘Industry 4.0’, Business & information systems engineering, vol. 6, no. 4, pp. 239–242, 2014.

[2] M. Rüßmann et al., ‘Industry 4.0: The future of productivity and growth in manufacturing industries’, Boston Consulting Group, vol. 9, no. 1, pp. 54–89, 2015.

[3] R. O. Lavrenov, E. A. Magid, F. Matsuno, M. M. Svinin, J. Suthakorn, “Development and implementation of spline-based path planning algorithm in ROS/Gazebo environment”, Tr. SPIIRAN, 18:1 (2019), 57–84.

[4] Moskvin, I., Lavrenov, R. Modeling Tracks and Controller for Servosila Engineer Robot. In Proceedings of 14th International Conference on Electromechanics and Robotics “Zavalishin's Readings”, 2020, pp. 411-422.

[5] J. Levinson et al., ‘Towards fully autonomous driving: Systems and algorithms’, in 2011 IEEE Intelligent Vehicles Symposium (IV), 2011, pp. 163–168.

[6] R. Manduchi, A. Castano, A. Talukder, and L. Matthies, ‘Obstacle detection and terrain classification for autonomous off-road navigation’, Autonomous robots, vol. 18, no. 1, pp. 81–102, 2005.

[7] M. S. Darms, P. E. Rybski, C. Baker, and C. Urmson, ‘Obstacle detection and tracking for the urban challenge’, IEEE Transactions on intelligent transportation systems, vol. 10, no. 3, pp. 475–485, 2009.

[8] E. Frazzoli, M. A. Dahleh, and E. Feron, ‘Real-time motion planning for agile autonomous vehicles’, Journal of guidance, control, and dynamics, vol. 25, no. 1, pp. 116–129, 2002.

[9] Y. Kuwata, J. Teo, S. Karaman, G. Fiore, E. Frazzoli, and J. How, ‘Motion planning in complex environments using closed-loop prediction’, in AIAA Guidance, Navigation and Control Conference and Exhibit, 2008, p. 7166.

[10] Lavrenov, R., Matsuno, F., Magid, E. Modified spline-based navigation: guaranteed safety for obstacle avoidance. In International Conference on Interactive Collaborative Robotics, 2017, pp. 123-133.

[11] Y. Kawabata et al., ‘Parking assist apparatus’, 2012.

[12] A. D. Shaffer, V. Stempnik, B. Choi, and M. Crawford, ‘Active park assist object detection’, 2017.

[13] C. Dorrer, ‘Automated driving at BMW–Solutions for today and tomorrow’, in 18. Internationales Stuttgarter Symposium, 2018, pp. 859–871.

[14] M. Trajkovic, A. J. Colmenarez, S. Gutta, and K. I. Trovato, ‘Computer vision based parking assistant’, 2004.

[15] Ibragimov, I. Z., Afanasyev, I. M. Comparison of ROS-based visual SLAM methods in homogeneous indoor environment. In 14th Workshop on Positioning, Navigation and Communications (WPNC), 2017, pp. 1-6.

[16] J. K. Suhr, H. G. Jung, ‘Fully-automatic recognition of various parking slot markings in Around View Monitor (AVM) image sequences’, International Conference on Intelligent Transportation Systems, 2012, pp. 1294–1299.

[17] J. K. Suhr and H. G. Jung, ‘Sensor fusion-based vacant parking slot detection and tracking’, IEEE transactions on intelligent transportation systems, vol. 15, no. 1, pp. 21–36, 2014.

[18] O. Sergiyenko, L. Burtseva, M. Bravo, I. G. Rendon, and V. Tyrsa, ‘Scanning vision system for mobile vehicle navigation’, in 2006 Multiconference on Electronics and Photonics, 2006, pp. 178–180.

[19] T. Lerch, M. MacGillivray, and T. Domina, ‘3D Laser Scanning: A Model of multidisciplinary research’, Journal of Textile and Apparel, Technology and Management, vol. 5, no. 4, pp. 1–8, 2007.

[20] S. Kato, E. Takeuchi, Y. Ishiguro, Y. Ninomiya, K. Takeda, and T. Hamada, ‘An open approach to autonomous vehicles’, IEEE Micro, vol. 35, no. 6, pp. 60–68, 2015.

[21] B. Lee, Y. Wei, and I. Y. Guo, ‘Automatic parking of self-driving car based on lidar’, The International Archives of the photogrammetry, remote sensing and spatial information sciences, vol. 42, 2017.

[22] D. O. Rubio, A. Lenskiy, and J.-H. Ryu, ‘Connected components for a fast and robust 2D LiDAR data segmentation’, in 2013 7th Asia Modelling Symposium, 2013, pp. 160–165.

[23] A. N. Catapang and M. Ramos, ‘Obstacle detection using a 2D LIDAR system for an Autonomous Vehicle’, in International Conference on Control System, Computing and Engineering (ICCSCE), 2016, pp. 441–445.

[24] T. Taipalus and J. Ahtiainen, ‘Human detection and tracking with knee-high mobile 2D LIDAR’, in 2011 IEEE International Conference on Robotics and Biomimetics, 2011, pp. 1672–1677.

[25] B. Abbyasov, R. Lavrenov, A. Zakiev, K. Yakovlev, M. Svinin, and E. Magid, “Automatic tool for gazebo world construction: from a grayscale image to a 3d solid model”, International Conference on Robotics and Automation (ICRA), 2020, pp. 7226-7232.

[26] K. Shabalina, A. Sagitov, K. Su, K.-H. Hsia, and E. Magid, ‘Avrora unior car-like robot in gazebo environment’, in International Conference on Artificial Life and Robotics (ICAROB), 2019, pp. 116–119.

[27] Shimchik, I., Sagitov, A., Afanasyev, I., Matsuno, F., and Magid, E. (2016). Golf cart prototype development and navigation simulation using ROS and Gazebo. In MATEC Web of Conferences, Vol. 75, p. 09005.

[28] R. J. Campello, D. Moulavi, A. Zimek, J. Sander, ‘Hierarchical density estimates for data clustering, visualization, and outlier detection’, ACM Transactions on Knowledge Discovery from Data, vol. 10, no. 1, pp. 1–51, 2015.

[29] M. Ankerst, M. M. Breunig, H.-P. Kriegel, and J. Sander, ‘OPTICS: ordering points to identify the clustering structure’, ACM Sigmod record, vol. 28, no. 2, pp. 49–60, 1999.

[30] D. A. Reynolds, ‘Gaussian Mixture Models.’, Encyclopedia of biometrics, vol. 741, 2009.

[31] K. Konstantinidis, ‘Development of a Detection and Tracking of Moving Vehicles system for 2D LIDAR sensors’, 2020.