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3D Object Detection for Autonomous Vehicles

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1. Introduction and Rationale

The dissertation is inspired by the vision of The School of Engineering, Computing and Mathematics Research *"Our focus is on user-inspired original research with real-world applications. We have a wide range of activities from model-driven system design and empirical software engineering through to web technologies, cloud computing and big data, digital forensics and computer vision."* Students on the MSc Data Analytics Oxford Brookes course can be involved with research in the following research group: Artificial Intelligence and Vision Research Group. – Oxford Brookes University [75]

- ### Subject topic area

The rapid advancement of technology has significantly increased the level of automation in road vehicles in recent years. Compared to conventional vehicles, autonomous vehicles promise considerably improved universal access, safety, efficiency, convenience, and cost savings. In a short time, car manufacturers have moved from advertising Advanced Driver Assistance Systems or automated parking assistance systems to commercial vehicles that offer a high level of automation inroads. This advancement would not have been possible without the improvement of artificial intelligence algorithms, which allow to extract knowledge from large amounts of real-world driving data and develop more vigorous control and perception systems. The dissertation research on object detection for autonomous driving has mainly focused on 3D point cloud from LiDAR and 2D data from the camera.

- ### Key Issues

> *"Rapid developments in CAV technology, and the new business models which will underpin their use, could fundamentally change the way people and goods move around in the future, offering huge potential benefits in safety, efficiency,*

and productivity. AI is a critical enabler of this future, and Formula Student – Artificial Intelligence (FS-AI) will help nurture talent on which the UK's industry, from exciting young start-ups to large corporations, will help realise this future for society." - Simon Shapcott, Head of Research & Development, Centre for Connected & Autonomous Vehicles [74].

FS-AI has been introduced to challenge student teams to develop an AI driver capable of controlling a purpose-designed FS car through a series of racing challenges [74].

The primary race consists of completing ten laps faster, around a track which is defined by small cones (228 × 335 mm). The left and right boundaries are marked with blue and yellow cones. The racetrack is a closed-circuit long up to 500 meters, minimum track width is 3 meters, and cones in the exact boundary line are spaced up to 5 meters apart. According to the FS-AI Ruleset, the racetrack might contain straight lines, chicanes, hairpin, multiple turns, and decreasing radius. This work aims to enable a race car to autonomously complete multiple laps of an unknown racetrack without any human intervention and in a single attempt.

- Aims, Objectives and Risk Management

The goal of the dissertation is to (1) detect the cones; (2) classify the colors (blue, yellow, orange); (3) measure the distance between the car and the cone. All the tasks must be completed in real-time end-to-end in the car.

The aim is to improve the performance of cones detection. This can be done by using LiDAR, Camera, or fused LiDAR and Camera.

The objectives

- studying literature review on LiDAR and camera cones detection

- setting simulation or actual car
- get the dataset to train algorithm(s) from simulation or actual car
- developing the algorithm(s)
- testing on simulation or actual car
- analysing performance

Risk management

The algorithm's performance will depend on the dataset from LiDAR or Camera, the dataset will be considered to extract from both actual car and simulation. The FSOCO dataset [71] or KITTI dataset [76] might be used to train object detection in the access limitation of the Covid-19 context. The goal is to run the algorithm on actual car, however, it can be run on simulation to test performance.

- The Ethics of Autonomous Vehicles

The self-driving car is the most technologically advanced innovation. However, like any new technology, some ethical issues are surrounding it.

Self-Driving Cars Are Ethical because autonomous cars are safer than human-controlled automobiles. In a 2015 report, McKinsey and Company showed evidence that autonomous cars will decrease car accidents by 90%, save thousands of lives and save up to $190 billion. The National Science Foundation found that with self-driving cars, improvements in traffic flow are boosted: "having a single self-driving car on the road can reduce congestion by influencing the traffic flow of at least 20 human-controlled automobiles around it". It leads to reduce total fuel consumption during traffic jams by 40% [73].

However, some people argue that arbitrary decisions are better than predetermined ones. Who holds the responsibility if the car inflicted accidents, the car manufacturer, the software engineer, or the driver? Also, it raises many security issues as self-driving cars hold large amounts of data, including where the driver and passenger have been, driver communication when mobile phones are hooked, and conversations in the vehicle between drivers and passengers [72].

- Brief description of activity

For the racing car to be completely autonomous, it is necessary to add sensors that allow environmental perception. Since all perception, decision-making, and control algorithms had to be implemented onboard, additional computation units has to be added. A pipeline redundancy is required to make the primary system become robust and reliable. Thus, two independent cognitive pipelines operating with two sensing methods have been developed, enabling robust object detection (specifical cone) and distance estimation.

LiDAR sensor is the first sensor modality which is mounted on a sensor plate in the vehicle's front center. This optimizes the points returns per cone, allowing more distant cones to be recognized. Because of its capacity to identify small plastic cones,a LiDAR was chosen over a Radar. The LiDAR sensor is chosen based on physical parameters such as horizontal, vertical resolution, and field-of-view. The sensor has a horizontal field-of-view of 360 degrees; however, the active field-of-view is only 270 degrees because the sensor plate and the vehicle obscure the remainder. The vertical resolution is the essential parameter in this application since it restricts the number of returns per cone, directly proportional to the distance at which cones can be observed.

For redundancy and robustness, a combination of sensors is applied to sense the surroundings accurately. A LiDAR-based algorithm is utilized to detect cones based on geometry data and a colour recognition algorithm based on LiDAR intensity.

Simultaneously, a camera-based algorithm is implemented to estimate the cone's location from stereo and monocular images.

The perception purpose is to deliver cone location and colour estimations in real-time. The SLAM module creates a map using these cone locations as landmarks, allowing the race-car to navigate autonomously.

- Intended deliverables

By the limited hardware, we will select which method is approachable and demonstrated by a racing scenario collected with RS 16 LiDAR and camera using Brookes autonomous racing car 2021.

2. Background Review

Based on the implemented sensors, environmental perception can be solved using LIDAR, a camera, or a combination of the two.

2.1. LiDAR

LIDAR refers to light detection and ranging device, which sends millions of light pulses per second in a well-designed pattern. With its rotating axis, it can create a dynamic, three-dimensional map of the environment. LIDAR is the heart of object detection for most existing autonomous vehicles [1]. The points returned by the LIDAR in a natural setting, however, are never perfect. Scanning point sparsity, missing points, and disorganized patterns are problems when dealing with LIDAR points. The surrounding environment contributes to the difficulty of perception by presenting random and irregular surfaces.

Representation

Point clouds, features, and grids are the three common representations of the points.

The point cloud-based method uses the raw sensor data and processing futher. This approach gives better environmental representation but increases processing time and reduces efficiency of memory. To mitigate this, a voxel-based filtering mechanism is usually used to reduce the amount of raw point cloud, e.g., [2,3].

Feature-based approaches start by extracting parametric aspects from the point cloud and then using those features to represent the environment. Lines [4] and surfaces [5] are two features that are often used. This technique uses the least amount of memory; however, it is frequently overly abstract, and the accuracy depends on the point cloud since not all environmental features can be accurately reproduced by the collection as mentioned above.

Grid-based method divides the area to small grids which are filled with information from the point cloud, forming a point neighbourhood [6]. This technique is memory-efficient and does not rely on predetermined features, as stated in [7]. The magnitude of the discretization, on the other hand, is not easy to assess. An adaptive octree was constructed in [8] to guide division from coarse to fine grids.

Segmentation Algorithms

Point cloud segmentation is grouping points into similar groups. Edge-based [9,10,11], attributes-based [15,16,17,18], region-based [12,13,14], model-based [19,20,21], and graph-based [22,23,24] are the five types of 3D point cloud segmentation techniques.

Detection Algorithm

VoxNet, a 3D convolutional neural network that classifies point clouds (in occupancy grid or volumetric representation), was proposed in [25]. In [26], the volumetric-based 3D CNN was enhanced by integrating data augmentation with multi-orientation pooling and putting auxiliary learning tasks on the portion of an object. In [27], from raw CAD data, a 3D Constitutional Deep Beliefs Network was suggested to acquire the distribution of complex 3D shapes through different object categories and arbitrary poses.

2.2. Vision

Road and on-road object detection are usually part of the perception system of for self-driving vehicle.

Lane Line Marking Detection

There are three common steps of the lane line detection:

(1) lane line feature extraction: colour [28,29] and edge detection [30,31], by l supervised learning algorithms [32], boost classification [33,34];
(2) fitting the pixels into different models: hyperbolas [35,36,37], straight lines [38,39], parabolas [40,41], zigzag line [42];
(3) vehicle posture estimation based on the fitted model. To ensure temporal continuity, a fourth-time integration steps may occur before the car pose estimate, in which the results of the current frame detection are used to drive the next search through filtering mechanisms, such as the particle filter [43,44,45] and the Kalman filter [46,47].

Road Surface Detection

The autonomous car uses road surface sensing to determine empty space where it can travel without colliding. The methods can be separated into: feature-based learning [48], feature-based detection [49,50], and deep learning [51,52,53,54,55].

The top five road detection performances all come with deep learning, as shown in the well-known database KITTI [56]. However, the disadvantages of deep learning methods are obvious: high CPU and memory are required, long processing-time, non-traceability, and a time-consuming ground truth annotation procedure.

On-Road Object Detection

For deep learning systems, the usual workflow is to produce a collection of proposal bounding boxes around the image, then send the proposal boxes through the CNN network to classify and fine-tune bounding box positions.

The first deep learning that combined the bounding box and detection into a single network and complete a training process was Faster-RCNN [57]. MS-CNN is a unified multi-scale deep learning network that the authors in [58] proposed. In [59], the authors trained the deep learning network to recover 2D and 3D information from the 2D image (Sub-CNN).

2.3. Fusion

The strengths and limitations of the sensors vary. To fully use the benefits of each sensor, sensors fusion approach is necessary. The mechanisms that have been used to fused LIDAR and camera are then followed by [60,61,62,63,64,65,66,67,68]. However, present fusion techniques are still in their infancy and cannot properly utilize all the data from both sensors. Moreover, those deep learning algorithms have not yet operated on fused camera and LIDAR data, and this extension might give extensively performance improvements over single sensor data.

3. Methodology and Resources

3.1. LiDAR-based

The LiDAR data is capitalized in two ways. First, the point cloud's 3D is used to detect cones on the racetrack and determine their distance with the car. Next, the intensity information is used to distinguish different coloured cones.

The sub-system is described as below.

1) Pre-Processing: The ground is removed based on the assumption of local flatness. Every point in a segment that is lower than the lowest point plus a threshold is eliminated.
2) Cone Reconstruction and Filtration: Remove the ground also remove about 64% of cone points. Thus, the Euclidean distance-based approach [69,70] reconstructs the area around the clusters. Those clusters are filtered to check if the number of the points in the cluster is matches the predicted number of points at the distance. The clusters which gone through the filter are then transmitted to estimate colour.
3) Colour Estimation: The colour is classified by using Convolutional Neural Network (CNN) by the intensity of point cloud. It is limited at 5 meters because of the point cloud thinness.

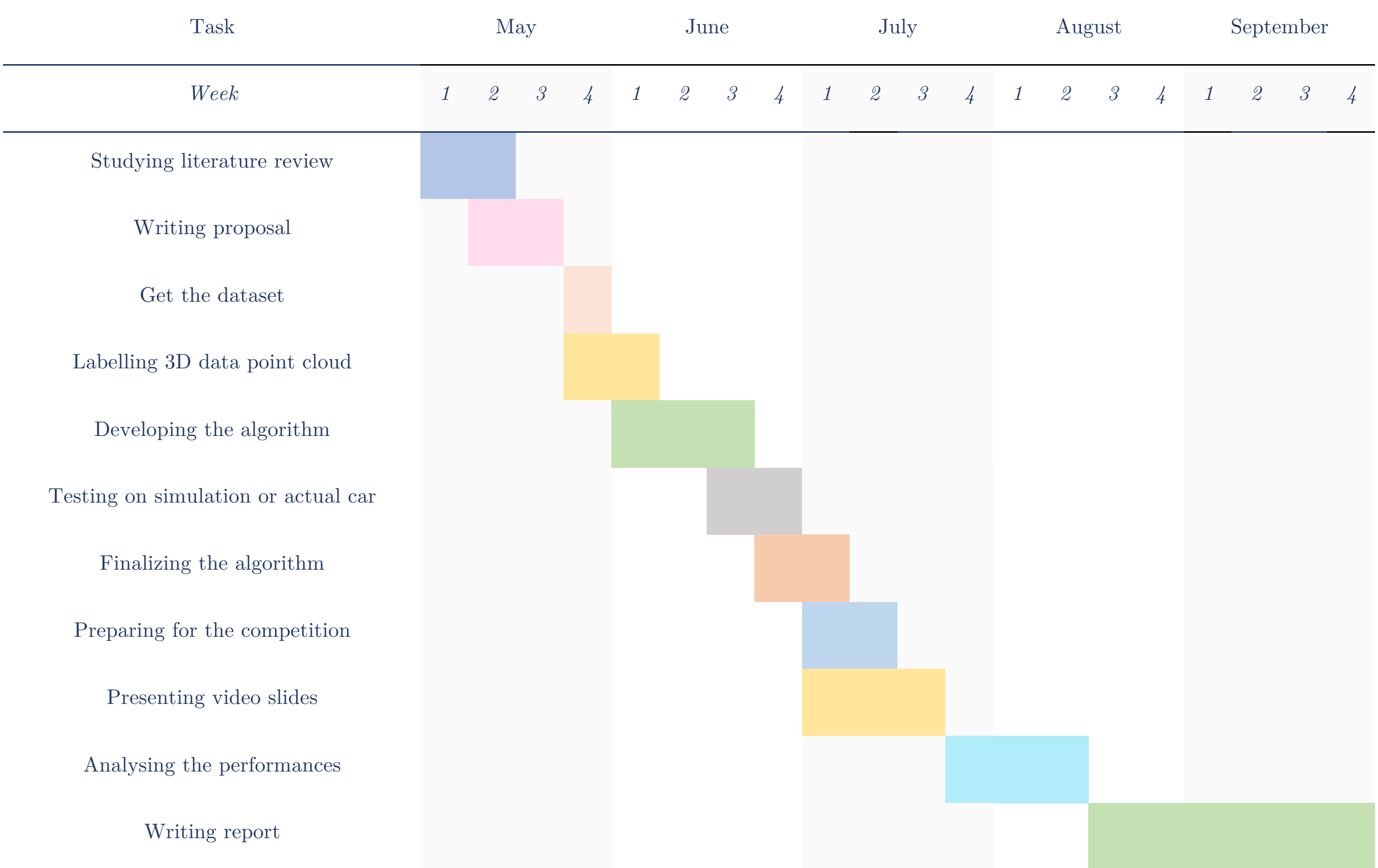
3.2. Camera-based

A real-time camera-based algorithm is deployed independent and parallel of the LiDAR to make the perception system robust. A real-time object detection YOLO or R-CNN is trained on different types of cones. After input images, the YOLO/R-CNN returns the bounding box around the detected cones along with the confidence count for each detection. The YOLO object detection might be chosen by its robust outputs and the ability to be fine-tuned with fewer data and due to the existence of pre-trained weights, which act as good priors during training.

3.3. Resources

A machine that contained 1.2 GHz Dual-Core Intel Core m3 processor with 8 GB 1867 MHz memory and Intel HD Graphics 615 1536 graphics memory is used. Device memory configuration: 250 GB SSD. As for the software, python 3.6, PyTorch, OpenCV, TensorFlow, Matplotlib, e.g., are used implementation and experiments.

4. Project Plan



In May, most works will be focused on getting used to LiDAR sensor software and hardware, label and prepare the 3D data point cloud. The following month is crucial as we need to find the algorithm, test the car, and finalize it to prepare for the mid-July competition. Alongside the competition, the 10 minutes presentation video is completed. Entire August and September are for the final report.

Bibliography

1. Pendleton, S., Andersen, H., Du, X., Shen, X., Meghjani, M., Eng, Y., Rus, D. and Ang, M. (2017). Perception, Planning, Control, and Coordination for Autonomous Vehicles. Machines, 5(1), p.6.

2. Zhao, G.; Xiao, X.; Yuan, J.; Ng, G.W. Fusion of 3D-LIDAR and camera data for scene parsing. J. Vis. Commun. Image Represent. 2014, 25, 165–183.

3. Moosmann, F.; Pink, O.; Stiller, C. Segmentation of 3D lidar data in non-flat urban environments using a local convexity criterion. In Proceedings of the 2009 IEEE Intelligent Vehicles Symposium, Xi'an, China, 3–5 June 2009; pp. 215–220.

4. Sack, D.; Burgard, W. A comparison of methods for line extraction from range data. In Proceedings of the 5th IFAC Symposium on Intelligent Autonomous Vehicles (IAV), Lisbon, Portugal, 5–7 July 2014; Volume 33.

5. Oliveira, M.; Santos, V.; Sappa, A.D.; Dias, P. Scene Representations for Autonomous Driving: An Approach Based on Polygonal Primitives. In Proceedings of the Robot 2015: Second Iberian Robotics Conference, Lisbon, Portugal, 19–21 November 2015; Springer: Berlin, Germany, 2016; pp. 503–515.

6. Wang, M.; Tseng, Y.H. Incremental segmentation of lidar point clouds with an octree-structured voxel space. Photogramm. Rec. 2011, 26, 32–57.

7. Asvadi, A.; Premebida, C.; Peixoto, P.; Nunes, U. 3D Lidar-based static and moving obstacle detection in driving environments: An approach based on voxels and multi-region ground planes. Robot. Auton. Syst. 2016, 83, 299–311

8. Vo, A.V.; Truong-Hong, L.; Laefer, D.F.; Bertolotto, M. Octree-based region growing for point cloud segmentation. ISPRS J. Photogramm. Remote Sens. 2015, 104, 88–100.

9. Yao, W.; Deng, Z.; Zhou, L. Road curb detection using 3D lidar and integral laser points for intelligent vehicles. In Proceedings of the 2012 Joint 6th International Conference on Soft Computing and Intelligent Systems (SCIS) and 13th International Symposium on Advanced Intelligent Systems (ISIS), Kobe, Japan, 20–24 November 2012; pp. 100–105.

10. Chen, X.; Deng, Z. Detection of Road Obstacles Using 3D Lidar Data via Road Plane Fitting. In Proceedings of the 2015 Chinese Intelligent Automation Conference, Fuzhou, China, 30 April 2015; Springer: Berlin, Germany, 2015; pp. 441–449.

11. Yu, Y.; Li, J.; Guan, H.; Wang, C.; Yu, J. Semiautomated extraction of street light poles from mobile LiDAR point clouds. IEEE Trans. Geosci. Remote Sens. 2015, 53, 1374–1386.

12. Zhou, Y.; Wang, D.; Xie, X.; Ren, Y.; Li, G.; Deng, Y.; Wang, Z. A fast and accurate segmentation method for ordered LiDAR point cloud of large-scale scenes. IEEE Geosci. Remote Sens. Lett. 2014, 11, 1981–1985.

13. Rusu, R.B. Semantic 3D object maps for everyday manipulation in human living environments. KI-Künstliche Intell. 2010, 24, 345–348.

14. Ioannou, Y.; Taati, B.; Harrap, R.; Greenspan, M. Difference of normals as a multi-scale operator in unorganized point clouds. In Proceedings of the 2012 Second International Conference on 3D Imaging, Modeling, Processing, Visualization & Transmission, Zurich, Switzerland, 13–15 October 2012; pp. 501–508.

15. Reddy, S.K.; Pal, P.K. Segmentation of point cloud from a 3D LIDAR using range difference between neighbouring beams. In Proceedings of the 2015 ACM Conference on Advances in Robotics, Goa, India, 2–4 July 2015; p. 55.

16. Burgard, W. Techniques for 3D Mapping. In Slides from SLAM Summer School 2009; SLAM Summer School: Sydney, Australia, 20–23 January 2009.

17. Hähnel, D.; Thrun, S. 3D Laser-based obstacle detection for autonomous driving. In Proceedings of the Abstract of the IEEE International Conference on Intelligent Robots and Systems (IROS), Nice, France, 22–26 Septempber 2008.

18. Montemerlo, M.; Becker, J.; Bhat, S.; Dahlkamp, H.; Dolgov, D.; Ettinger, S.; Haehnel, D.; Hilden, T.; Hoffmann, G.; Huhnke, B.; et al. Junior: The stanford entry in the urban challenge. J. Field Robot. 2008, 25, 569–597.

19. Azim, A.; Aycard, O. Layer-based supervised classification of moving objects in outdoor dynamic environment using 3D laser scanner. In Proceedings of the 2014 IEEE Intelligent Vehicles Symposium Proceedings, Dearborn, MI, USA, 8–11 June 2014; pp. 1408–1414.

20. Asvadi, A.; Peixoto, P.; Nunes, U. Two-Stage Static/Dynamic Environment Modeling Using Voxel Representation. In Proceedings of the Robot 2015: Second Iberian Robotics Conference, Lisbon, Portugal, 19–21 November 2015; Springer: Berlin, Germany, 2016; pp. 465–476.

21. Oniga, F.; Nedevschi, S. Processing dense stereo data using elevation maps: Road surface, traffic isle, and obstacle detection. IEEE Trans. Veh. Technol. 2010, 59, 1172–1182.

22. Vosselman, G.; Gorte, B.G.; Sithole, G.; Rabbani, T. Recognising structure in laser scanner point clouds. ISPRS Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2004, 46, 33–38.

23. Tarsha-Kurdi, F.; Landes, T.; Grussenmeyer, P. Hough-transform and extended ransac algorithms for automatic detection of 3d building roof planes from lidar data. In Proceedings of the ISPRS Workshop on Laser Scanning, Espoo, Finland, 12–14 September 2007; Volume 36, pp. 407–412.

24. Rabbani, T.; Van Den Heuvel, F. Efficient hough transform for automatic detection of cylinders in point clouds. ISPRS WG III/3, III/4 2005, 3, 60–65.

25. Maturana, D.; Scherer, S. Voxnet: A 3d convolutional neural network for real-time object recognition. In Proceedings of the 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Hamburg, Germany, 28 September–3 October 2015; pp. 922–928.

26. Qi, C.R.; Su, H.; Niessner, M.; Dai, A.; Yan, M.; Guibas, L.J. Volumetric and Multi-View CNNs for Object Classification on 3D Data. arXiv 2016. [Google Scholar]

27. Wu, Z.; Song, S.; Khosla, A.; Yu, F.; Zhang, L.; Tang, X.; Xiao, J. 3D shapenets: A deep representation for volumetric shapes. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Boston, MA, USA, 7–12 June 2015; pp. 1912–1920.

28. Tapia-Espinoza, R.; Torres-Torriti, M. A comparison of gradient versus color and texture analysis for lane detection and tracking. In Proceedings of the 2009 6th Latin American Robotics Symposium (LARS), Valparaiso, Chile, 29–30 October 2009; pp. 1–6.

29. Sun, T.Y.; Tsai, S.J.; Chan, V. HSI color model based lane-marking detection. In Proceedings of the Intelligent Transportation Systems Conference, ITSC'06, Toronto, ON, Canada, 17–20 September 2006; pp. 1168–1172.

30. Nedevschi, S.; Schmidt, R.; Graf, T.; Danescu, R.; Frentiu, D.; Marita, T.; Oniga, F.; Pocol, C. 3D lane detection system based on stereovision. In Proceedings of the 7th International IEEE Conference on Intelligent Transportation Systems, Washington, DC, USA, 3–6 October 2004; pp. 161–166.

31. Li, Q.; Zheng, N.; Cheng, H. An adaptive approach to lane markings detection. In Proceedings of the 2003 IEEE International Conference on Intelligent Transportation Systems, Shanghai, China, 12–15 October 2003; Volume 1, pp. 510–514.

32. Kim, Z. Robust lane detection and tracking in challenging scenarios. IEEE Trans. Intell. Transp. Syst. 2008, 9, 16–26.

33. Gopalan, R.; Hong, T.; Shneier, M.; Chellappa, R. A learning approach towards detection and tracking of lane markings. IEEE Trans. Intell. Transp. Syst. 2012, 13, 1088–1098.

34. Fritsch, J.; Kuhnl, T.; Kummert, F. Monocular road terrain detection by combining visual and spatial information. IEEE Trans. Intell. Transp. Syst. 2014, 15, 1586–1596.

35. Sivaraman, S.; Trivedi, M.M. Integrated lane and vehicle detection, localization, and tracking: A synergistic approach. IEEE Trans. Intell. Transp. Syst. 2013, 14, 906–917.

36. Du, X.; Tan, K.K. Vision-based approach towards lane line detection and vehicle localization. Mach. Vis. Appl.2015, 27, 1–17.

37. Du, X.; Tan, K.K.; Htet, K.K.K. Vision-based lane line detection for autonomous vehicle navigation and guidance. In Proceedings of the 2015 10th Asian Control Conference (ASCC), Sabah, Malaysia, 31 May–3 June 2015; pp. 3139–3143.

38. Kang, D.J.; Jung, M.H. Road lane segmentation using dynamic programming for active safety vehicles. Pattern Recognit. Lett. 2003, 24, 3177–3185.

39. Kum, C.H.; Cho, D.C.; Ra, M.S.; Kim, W.Y. Lane detection system with around view monitoring for intelligent vehicle. In Proceedings of the 2013 International. SoC Design Conference (ISOCC), Busan, Korea, 17–19 November 2013; pp. 215–218.

40. Cui, G.; Wang, J.; Li, J. Robust multilane detection and tracking in urban scenarios based on LIDAR and mono-vision. IET Image Process. 2014, 8, 269–279.

41. Lu, W.; Seignez, E.; Rodriguez, F.S.A.; Reynaud, R. Lane marking based vehicle localization using particle filter and multi-kernel estimation. In Proceedings of the 2014 13th International Conference on Control Automation Robotics & Vision (ICARCV), Singapore, 10–12 December 2014; pp. 601–606.

42. Du, X.; Tan, K.K. Comprehensive and practical vision system for self-driving vehicle lane-level localization. IEEE Trans. Image Process. 2016, 25, 2075–2088.

43. Kim, Z. Robust lane detection and tracking in challenging scenarios. IEEE Trans. Intell. Transp. Syst. 2008, 9, 16–26.

44. Du, X.; Tan, K.K. Comprehensive and practical vision system for self-driving vehicle lane-level localization. IEEE Trans. Image Process. 2016, 25, 2075–2088

45. Danescu, R.; Nedevschi, S. Probabilistic lane tracking in difficult road scenarios using stereovision. IEEE Trans. Intell. Transp. Syst. 2009, 10, 272–282.

46. Nedevschi, S.; Schmidt, R.; Graf, T.; Danescu, R.; Frentiu, D.; Marita, T.; Oniga, F.; Pocol, C. 3D lane detection system based on stereovision. In Proceedings of the 7th International IEEE Conference on Intelligent Transportation Systems, Washington, DC, USA, 3–6 October 2004; pp. 161–166.

47. Borkar, A.; Hayes, M.; Smith, M.T. A novel lane detection system with efficient ground truth generation. IEEE Trans. Intell. Transp. Syst. 2012, 13, 365–374.

48. Mendes, C.C.T.; Frémont, V.; Wolf, D.F. Vision-Based Road Detection using Contextual Blocks. arXiv 2015

49. Wedel, A.; Badino, H.; Rabe, C.; Loose, H.; Franke, U.; Cremers, D. B-spline modeling of road surfaces with an application to free-space estimation. IEEE Trans. Intell. Transp. Syst. 2009, 10, 572–583.

50. Ladickỳ, L.; Sturgess, P.; Russell, C.; Sengupta, S.; Bastanlar, Y.; Clocksin, W.; Torr, P.H. Joint optimization for object class segmentation and dense stereo reconstruction. Int. J. Comput. Vis. 2012, 100, 122–133.

51. Mendes, C.C.T.; Frémont, V.; Wolf, D.F. Exploiting Fully Convolutional Neural Networks for Fast Road Detection. In 2016 IEEE International Conference on Robotics and Automation (ICRA), Stockholm, Sweden, 16–21 May 2016.

52. Brust, C.A.; Sickert, S.; Simon, M.; Rodner, E.; Denzler, J. Convolutional patch networks with spatial prior for road detection and urban scene understanding. arXiv 2015. [Google Scholar]

53. Mohan, R. Deep deconvolutional networks for scene parsing. arXiv 2014.

54. Oliveira, G.L.; Burgard, W.; Brox, T. Efficient deep models for monocular road segmentation. In Proceedings of the 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Daejeon, Korea, 9–14 October 2016; pp. 4885–4891.

55. Laddha, A.; Kocamaz, M.K.; Navarro-Serment, L.E.; Hebert, M. Map-supervised road detection. In Proceedings of the 2016 IEEE Intelligent Vehicles Symposium (IV), Gotenburg, Sweden, 19–22 June 2016; pp. 118–123.

56. Fritsch, J.; Kuehnl, T.; Geiger, A. A New Performance Measure and Evaluation Benchmark for Road Detection Algorithms. In Proceedings of the International Conference on Intelligent Transportation Systems (ITSC), The Hague, The Netherlands, 6–9 October 2013.

57. Ren, S.; He, K.; Girshick, R.; Sun, J. Faster R-CNN: Towards real-time object detection with region proposal networks. In Proceedings of the Advances in Neural Information Processing Systems, Montreal, ON, Canada, 7–12 December 2015; pp. 91–99.

58. Cai, Z.; Fan, Q.; Feris, R.S.; Vasconcelos, N. A unified multi-scale deep convolutional neural network for fast object detection. In European Conference on Computer Vision; Springer: Berlin, Germany, 2016; pp. 354–370.

59. Xiang, Y.; Choi, W.; Lin, Y.; Savarese, S. Subcategory-aware Convolutional Neural Networks for Object Proposals and Detection. arXiv 2016.

60. Hall, D.L.; Llinas, J. An introduction to multisensor data fusion. Proc. IEEE 1997, 85, 6–23.

61. Schoenberg, J.R.; Nathan, A.; Campbell, M. Segmentation of dense range information in complex urban scenes. In Proceedings of the 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Taipei, Taiwan, 18–22 October 2010; pp. 2033–2038.

62. Xiao, L.; Dai, B.; Liu, D.; Hu, T.; Wu, T. CRF based road detection with multi-sensor fusion. In Proceedings of the 2015 IEEE Intelligent Vehicles Symposium (IV), Seoul, Korea, 28 June–1 July 2015; pp. 192–198.

63. Premebida, C.; Carreira, J.; Batista, J.; Nunes, U. Pedestrian detection combining rgb and dense lidar data. In Proceedings of the 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems, Chicago, IL, USA, 14–18 September 2014; pp. 4112–4117.

64. Felzenszwalb, P.F.; Girshick, R.B.; McAllester, D.; Ramanan, D. Object detection with discriminatively trained part-based models. IEEE Trans. Pattern Anal. Mach. Intell. 2010, 32, 1627–1645.

65. Premebida, C.; Monteiro, G.; Nunes, U.; Peixoto, P. A lidar and vision-based approach for pedestrian and vehicle detection and tracking. In Proceedings of the 2007 IEEE Intelligent Transportation Systems Conference, Bellevue, WA, USA, 30 September–03 October 2007; pp. 1044–1049.

66. Premebida, C.; Nunes, U. A multi-target tracking and GMM-classifier for intelligent vehicles. In Proceedings of the 2006 IEEE Intelligent Transportation Systems Conference, Toronto, ON, Canada, 17–20 September 2006; pp. 313–318.

67. Eitel, A.; Springenberg, J.T.; Spinello, L.; Riedmiller, M.; Burgard, W. Multimodal deep learning for robust rgb-d object recognition. In Proceedings of the 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Hamburg, Germany, 28 September–2 October 2015; pp. 681–687.

68. Schlosser, J.; Chow, C.K.; Kira, Z. Fusing LIDAR and images for pedestrian detection using convolutional neural networks. In Proceedings of the 2016 IEEE International Conference on Robotics and Automation (ICRA), Stockholm, Sweden, 16–21 May 2016; pp. 2198–2205.

69. Bertrand Douillard et al. "On the segmentation of 3D LIDAR point clouds". In: Robotics and Automa- tion (ICRA), 2011 IEEE International Conference on. IEEE. 2011, pp. 2798–2805.

70. Renaud Dube´ et al. "Segmatch: Segment based place recognition in 3d point clouds". In: Robotics and Automation (ICRA), 2017 IEEE International Conference on. IEEE. 2017, pp. 5266–5272.

71. Dodel, D., Schötz, M. and Vödisch, N. (2021). FSOCO: The Formula Student Objects in Context Dataset. arXiv:2012.07139 [cs]. [online] Available at: https://arxiv.org/abs/2012.07139

72. MBA, A.L. (2020). The Ethics of Self-Driving Cars. [online] Medium. Available at: https://towardsdatascience.com/the-ethics-of-self-driving-cars-efaaaaf9e320.

73. Dalvin Brown (2018). How self-driving car or adaptive cruise control could ease traffic jams. [online] USA TODAY. Available at: https://eu.usatoday.com/story/money/2018/07/03/self-driving-reduces-traffic-jams-study-says/741985002/.

74. www.imeche.org. (n.d.). FS AI. [online] Available at: https://www.imeche.org/events/formula-student/team-information/fs-ai.

75. Oxford Brookes University. (n.d.). MSc in Data Analytics at Oxford Brookes University. [online] Available at: https://www.brookes.ac.uk/courses/postgraduate/data-analytics/ [Accessed 27 May 2021].

76. www.cvlibs.net. (n.d.). The KITTI Vision Benchmark Suite. [online] Available at: http://www.cvlibs.net/datasets/kitti/index.php [Accessed 28 May 2021].