Lit Review

Depth cameras are essential for providing both depth and contextual information about the environment, which is a crucial aspect of autonomous vehicles. The Intel RealSense D435 camera utilises stereo vision technology by capturing two images simultaneously from slightly different angles. The disparity between corresponding pixels is then used to calculate depth. Additionally, the D435 camera incorporates an infrared (IR) projector to enhance depth perception in low-texture environments where standard visual cues are insufficient [a].

A key advantage of depth cameras is their ability to provide detailed contextual awareness of surroundings, which makes them an integral part in object avoidance for autonomous vehicles. Stereo vision resembles human vision and hence enables the detection of obstacles such as other vehicles [b][c] and pedestrians[d], which is crucial for safe driving. From stereo data, regions of interest can be identified, objects classified, and 3D point clouds generated. This offers a comprehensive understanding of the environment.

In addition to object detection, cameras can capture visual cues such as lane markings [e][h], which assist in estimating the road layout and understanding the traffic scene. In the cases where visual data is ambiguous, probabilistic models have been employed to improve decision-making, ensuring a smoother, more reliable experience [f][g]. Cameras provide autonomous vehicles with the ability to make decisions like human drivers as they can detect, recognise, and extract valuable information. Furthermore, cameras have also been adapted for 3D mapping for aiding navigation and localisation [i].

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[h] Z. Rahman and B. T. Morris, 'LVLane: Deep Learning for Lane Detection and Classification in Challenging Conditions', in *2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC)*, 2023, pp. 3901–3907.

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[i] C. Häne *et al.*, '3D visual perception for self-driving cars using a multi-camera system: Calibration, mapping, localization, and obstacle detection', *Image and Vision Computing*, vol. 68, pp. 14–27, 2017.

https://www.sciencedirect.com/science/article/pii/S0262885617301117

[j] https://ieeexplore.ieee.org/document/8330044

1. Implement individual sensors (Camera, LiDAR, Radar, IR)
   a. Collect and process the raw data from each sensor
   b. Develop the algorithms to interpret the sensor data and extract essential information
   c. Conduct sensor calibration and performance testing to understand the limitations of the sensor and to estimate errors
2. Achieve sensor fusion between the sensors
   a. Preprocess the raw data to ensure compatibility for fusion
   b. Implement and test sensor fusion techniques, starting with one sensor at a time (e.g. Camera-LiDAR) and then progressively add additional sensors until all sensors are incorporated (Camera-LiDAR-Radar-IR).
   c. Achieve time synchronisation with the sensors
3. Evaluate obstacle detection, object tracking and SLAM algorithms
   a. Develop and apply algorithms to detect objects and to navigate an unknown environment.
   b. Test and compare the performance of various algorithms, measuring the accuracy, robustness, and computational efficiency.

Allocation of Team Resources

Catherine

- Radar set up
- Radar data interpretation/preprocessing

Maksym

- LiDAR set up
- LiDAR data interpretation/preprocessing

Maxim

- Sensor fusion

Rebecca

- Camera set up
- Camera data interpretation/preprocessing

Extras

- Physical vehicle set up (incl. 3D printing)
- SLAM and localisation
- IR sensor
- Object detection/classification