
Car Driving Without Cameras

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EXECUTIVE SUMMARY

The need for robust object detection in 3D point clouds has greatly increased with the ongoing push for autonomous vehicles (AVs). Most of these systems use Light Detection and Ranging (LiDAR), cameras or a combination of both in order to perform object detection. LiDAR presents objects as point clouds in a 3D space thus offering critical shape information of objects in view. However, this representation is sparse. As a result, LiDAR-based detection performs poorly as compared to multimodal methods that have helped overcome this. Nonetheless, multimodal methods are often complex to set up and synchronise with the cost of components running into thousands of pounds. In light of this, reducing the number of sensors while still maintaining or even improving the accuracy has become a topic of interest by industry players who are developing AVs. With the cost of LiDAR declining following recent improvements in solid-state LiDAR technology, dropping cameras in favour of LiDAR has become more plausible. As compared to cameras that suffer drawbacks such as visibility issues in extreme weather, LiDAR is extremely robust and accurate in various conditions.

This project will be 65% type I (Software Development) and 35% type II (Theoretical).

DEDICATION AND ACKNOWLEDGEMENTS

Here goes the dedication.

AUTHOR'S DECLARATION

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

SIGNED: DATE:

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INTRODUCTION

Accelerated by recent advancements in technology, the prospect of Autonomous Vehicles (AVs) driving in public roads is becoming more and more a reality. As this is an emerging field, there are numerous variations of implementations by different companies. Arguably, a key characteristic of these implementations is a large number of perception sensors including cameras, radars and Light detection ranging sensors(LiDAR). This is necessary for mapping the environment around the vehicle in order to safely navigate. In addition to the high cost of these sensors, fusing their input and running object detection models requires powerful processing units such as GPUs. This process consumes a lot of power and generates a lot of heat.

In an effort to reduce the cost, companies are exploring different ways to reduce the number of sensors while still achieving a high level of navigational accuracy and safety. Extensive research has been undertaken to assess the performance of these sensors in different weather contexts such as in rain, fog and snow. However, the performance of these sensors in different area contexts, that is urban or non-urban, has not been exhaustively explored. Urban environments tend to have more dynamic objects and scenarios as compared to the static ones in most non-urban areas. As such, it can be argued that depending on the area context, the sensor configuration could be modified.

You probably need to present a succinct critique comment for each of the top 4 pieces of related work (which 'coincidentally' are limitations you try to address in your aims). Why do we need to test with different datasets? different models? Why is this important scientifically and also for companies developing lidar-onlu systems?

In order to investigate this, state of the art object detection models will be considered. Firstly, VoxelNet [42]], a LiDAR only model that uses point clouds as input. Secondly, Aggregated View Object Detection(AVOD) [20], a multimodal model that fuses image and point cloud data. Both model implementations were available on GitHub and were modified in order to align with the

aims of this project.

1.1 Aims and Objectives

Following the motivations in the presented discussion , the performance of LiDAR only and multimodal(LiDAR and Camera) models in different contexts will be investigated with the aim of reducing the number of sensors in AVs. To achieve this aim, the following objectives will need to be fulfilled:

1. Detect and characterise the context of images and point clouds.
2. Evaluate the performance of both models in different contexts.
3. Validate performance of VoxelNet(single sensor) on a custom dataset.

1.2 Deliverables

The deliverables are:

- **Image and LiDAR Context Classifier.** Available as Jupyter interactive notebooks including pre-trained models.
- **Custom VoxelNet Model** Modified VoxelNet model including interactive notebooks for training, testing and validating the model.
- **Custom AVOD Model** Modified AVOD model including interactive notebooks for training, testing and validating the model.
- **Validation Dataset** Point Cloud dataset obtained from the University of Bristol Smart Internet Lab working on connected and AVs. Tools to convert the dataset into a trainable input for VoxelNet will be provided as well.
- **Evaluation report.** The following topics will be discussed.
 1. A review of related research and implementations tackling object detection in AVs.
 2. Economic, ethical and legal analysis of the implementation and its potential impact on the development of AVs.
 3. Evaluation of context classifiers and object detection models in different contexts.
 4. Validation of VoxelNet using the Smart Internet Lab dataset.

1.3 Report structure

This report will consist of five main chapters.

- Chapter 2 discusses the different components of AVs, current implementations in the industry, a background on the research that has been undertaken in the field of object detection.
- Chapter 3 details the project execution and the methods undertaken to achieve the objectives.
- In Chapter 4, the results following evaluation of the methods will be discussed and analysed.
- Finally, a concluding chapter discusses the major findings, whether the objectives were achieved and a justification of their implications.

BACKGROUND

The idea of autonomous vehicles(AVs) is not new. As early as 2005, DARPA had invested heavily in the creation of unmanned trucks and organised for the Urban Challenge [6] to allow for different teams to showcase their unmanned vehicles. However, due to the challenges such as low computational power and underdeveloped AI and ML systems, the resulting implementations were not practical and had a high fault rate of 1 fault in 100 miles compared to the human fault rate of around 1 in 100 million miles. Nonetheless, from this challenge, it was clear that the prospect of AVs was plausible and indeed possible.

Currently, AVs are divided into five levels of autonomy as defined by the Society of Automotive Engineers(SAE):

SAE level	Description
0	No AV control systems. An example is blind spot indicators.
1	Basic driver assistance built into vehicle design. An example is the cruise control function.
2	Basic AV control systems. Driver required to monitor the environment and take back control if need be. A good example is the Tesla Autopilot.
3	AVs can safely navigate and drive within mapped environment. Driver required to monitor the environment and take back control if need be.
4	Highly autonomous control capable of handling most conditions but the driver has the option to take control. Renault ISymbioz is an example of a level 4 AV.
5	Completely autonomous with zero human involvement.

2.1 Components of an AV

- **LiDAR** - LiDAR provides highly detailed 3D information about the environment around the vehicle and objects in it. LiDAR operates by sending out pulses of lasers and recording

the reflections of the pulses from objects. By comparing this with the time taken for the lasers to be reflected(time of flight) and their direction, the distance of these objects can be calculated and mapped in a point cloud.

LiDAR units require complex optical systems that are expensive to build. As a result, they are the most expensive sensors in AVs with the top end such as Velodyne HDL-64E shown in figure 21 costing more than 50,000\$. In a bid to reduce the cost of LiDAR units, different companies are exploring different design methods that are cheaper but still able to offer the same performance as the top end LiDAR units such as solid state LiDAR¹.



Figure 21: Velodyne LiDAR family. From left: Velodyne HDL-64E , HDL-32E , VLP-16

- **Cameras** - Cameras mounted on the vehicle are used for classification and identification of various objects on the road. Cameras can also be used to create 3D maps of the surrounding environment. By combining two cameras, a stereo image can be captured that provides depth information. Alternatively, by combining a camera and IR Laser sensor for depth estimation, RGB-D [17] images are obtained and mapped in a point cloud.
- **Position Estimators** - Position estimators are a group of sensors used for navigation of the vehicle. These include GPS systems, odometers and gyrometers.

¹See appendix ??

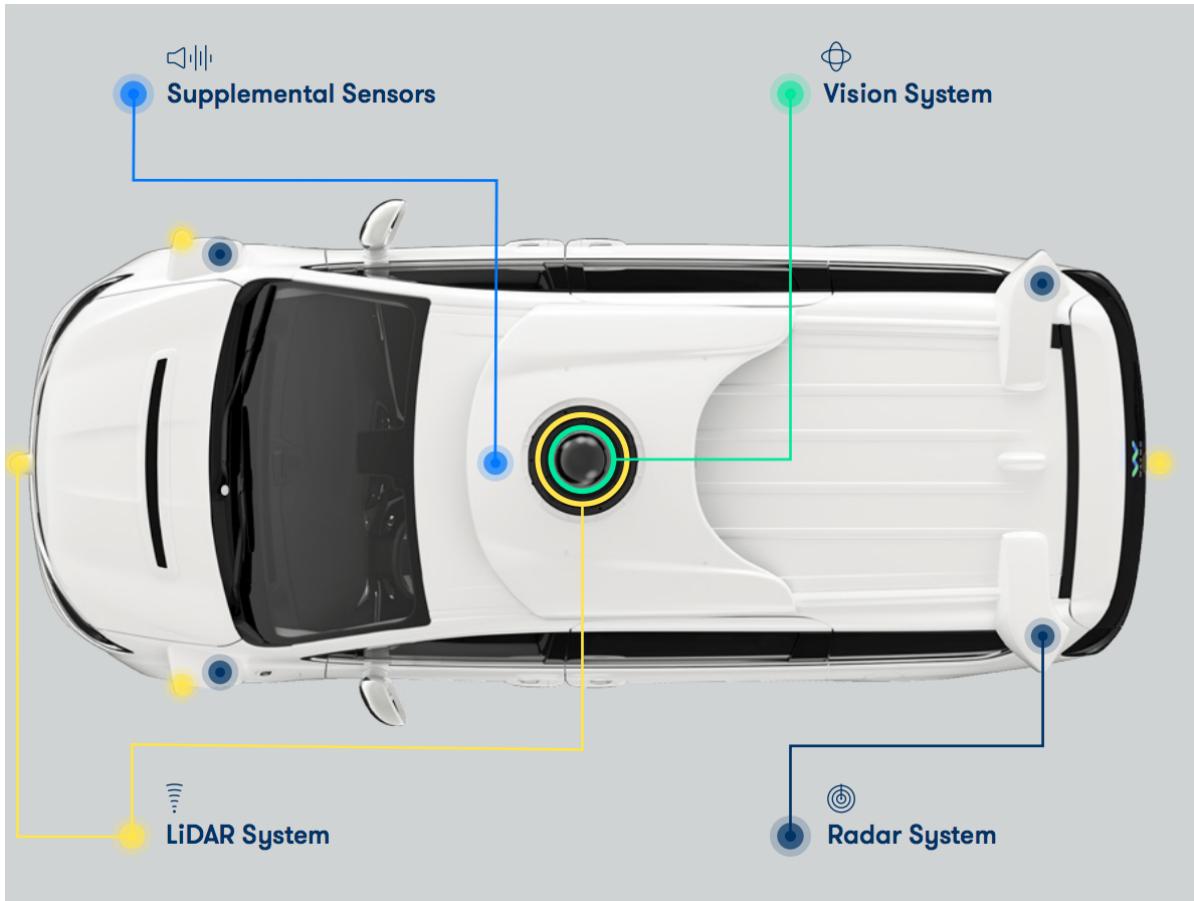


Figure 22: Components of Waymo's Self Driving Car [39]

- **Distance Sensors** - Distance sensors such as radars and sonars are important for gauging the distance of objects on the road. Radars are the most commonly used distance sensors and they work by transmitting radio waves and recording the reflected radio waves from objects. As compared to cameras and LiDARs, radars work well in a variety of low visibility scenarios such as poor weather. However, the reflectivity of these radio waves depends on the nature of objects, their size, absorbtion characteristics and the transmitting power. As such, it is may not be effective for detecting objects with low absorbtion characteristics such as pedestrians and animals.
- **Processing Unit** - In order to process all the data from sensors on the vehicle, AVs require powerful processing units to do so in real time. Most ML/AI algorithms used for detecting and identifying objects from LiDAR and camera data demand large amounts of processing power. This is achieved through the use of CPUs, GPUs, Field Programmable Gate Arrays(FPGA)[5], Application Specific Integrated Circuits(ASICs)[37] or combinations with each other.

AVs have three main modes of operation namely,

- **Perception** - This is the first step which involves processing the input from the sensors. In this mode tasks such as object detection and tracking, lane detection, traffic sign detection and recognition are performed.
- **Planning** - This is the next step after detection and recognition tasks are performed . In this stage route and trajectory planning algorithms are run to plan how the vehicle should navigate in the immediate environment as well as a route to a target location. These algorithms are required to handle complex situations to ensure safety of the passengers and other road users.
- **Control** - This stage involves the execution of plans created in the planning stage. This stage is crucial as the actuators involved in steering and movement have to be able to be able to accurately follow the plans. This involves calculation of energy and forces. At this stage the trajectories and movement of other road users and objects have to be calculated in order to anticipate and avoid any accidents.

2.2 Industrial Approaches

In order to be viable, AVs need to meet a few constraints as discussed in [24].

- **Performance**

At the moment there are no clear regulations as to how fast the perception, planning and control pipeline should be. However according to research by Brown et al. [4], humans take around 600 ms to respond and brake when expecting an interruption, however this figure shoots to 850 ms when an unexpected situation arises. In addition, Newell et al [28], established that the fastest human response time is between 100-150ms. These figures can be used as a baseline while developing a pipeline. In this pipeline, there are two factors to consider, namely the frame rate (frequency of the data from sensors) and the processing latency (time taken to process data). As such, an AV system should be able to react within 100ms, that is, faster than the human response time.

- **Storage**

AVs should be able to store maps of different areas with fine granularity for accuracy during localisation. As a result, the storage of these maps can run into tens of Terabytes. Despite recent advances in cloud technology and the emergence of 5G connectivity that is significantly fast. Downloading these maps would take significant time and would also render the car unusable in case of no internet connectivity. As such, the vehicles should have enough storage to store these maps locally.



Figure 23: AV Leaderboard. Navigant Research[33]

- **Power**

Most of the major industry players have moved to electric-vehicles for their AV systems. Depending on the equipment and sensor configurations used in these systems, the power usage can range from 500 watts to 1.5 kilowatts. Given that the AVs have limited battery capacity, heavy power consumption by these systems can lead to poor driving ranges hence making the cars less viable. As such the configuration of these systems has to be carefully considered to ensure a reasonable driving range.

- **Thermal**

Processing components in the AV systems such as CPUs and GPUs require a significant amount of energy to cool. This is necessary to ensure that they operate within their recommended thermal operating range. Failure to do so could result in the failure of these systems. As such, additional cooling systems have to be installed in the vehicle in order to ensure this.

Following the discussion above, the next subsections will review how different industry players are implementing their AV systems with special focus to the issue of perception

2.2.1 Camera

Mobileye[27], is one of the top contenders in the development of camera only AVs. It was recently acquired by Intel and believes that AVs should be able to accurately and safely navigate using cameras only given the fact that humans are able to do so with vision only. Previously, MobilEye was a supplier of vision systems for Advanced Driver Assistance Systems and had a partnership

with Tesla to supply their vision systems prior being acquired by Intel. Given their extensive background in developing these vision systems, the partnership with Intel aims to develop a complete autonomous driving package.[18]

2.2.2 Camera and Radar

Another major contender that is using the camera and radar configuration is Tesla. Elon Musk, the founder, believes that LiDAR is not necessary for AV perception. However, just recently, a Tesla vehicle was involved in a crash while in 'autopilot' mode that resulted in the loss of life. A major attributing factor to this accident was caused by the fact that bright sunlight blinded the camera thus causing the vehicle not to detect a white truck that was ahead of it. The radar was also unable to detect it thus leading to a collision. LiDAR on the other hand, would have been able to detect the truck despite the poor visibility. This illustrates how unreliable this configuration can be.

2.2.3 LiDAR, Camera and Radar

This configuration is used by most of the leading industry players such as Waymo and GM Cruise. This configuration has proven to be robust and accurate. However, in order to process the amount of fused data, they require large amounts of processing power which in turn may lead to increased power usage.

2.3 Object Detection

2.3.1 Object Detection using Classic Computer Vision Methods

Classic computer vision methods have advanced over the years from simple algorithms such as SIFT[25] and SURF[2] which use descriptors to detect interesting points in images for object detection to much higher level representations such as the Histogram of Gradient(HOG)[11] or Haar Features[38] that were used in classifiers. However, these methods have been unreliable, slow and not as accurate. In addition these features are only able to model 2D data. 3D methods such as Intrinsic Shape Signatures(ISS)[], NARF[] and Uniform Sampling have since been developed but are lacking in terms speed. Furthermore, these feature detectors have to be hand-crafted manually which is a tedious process. As a result, they are rarely used in real-time AV applications due to their speed and accuracy.

2.3.2 Object Detection using Deep Learning

The emergence and development of Deep Neural Networks such as Convolutional Neural Networks (CNNs)[21] has offset the reliance of classical methods of object detection in images by allowing for features to be automatically learnt by the network without the need for manual

feature extraction. This is due to the fact that these networks have numerous number of deep layers that are able to capture these features.

Monocular and Stereo Vision

Monocular vision is derived from a single camera. This representation is 2D and lacks depth information. Mono3D by Chen et al [8] is a state of the art object detection model that uses monocular images where they were fed through a CNN and the resulting 2D object proposals were extruded into 3D bounding boxes by performing segmentation.

Stereo vision involves calibrating two cameras intrinsically and extrinsically by matching similar points in images from both cameras. Using the resulting stereo image, it is possible to estimate the depth of objects in the image. However the accuracy of this depends on a few factors such as the resolution, camera quality, lens distortion and the calibration algorithm. 3DOP [9]

LiDAR+Camera

By fusing input from a monocular image and point clouds, it is possible to extract depth information from the images. Chen et al further reiterated their monocular approach into MV3D[10] a multiview 3D object detection network. In their work, they were able to fuse LiDAR and camera input to create a bird's eye view of the surrounding environment and further perform object detection of features.

LiDAR

Point cloud object detection is particularly challenging as established 3D object detection methods for images cannot be applied to point clouds. Point clouds are a set of geometric points in a euclidean space. They are unordered in nature and this presents a particular problem to deep learning methods as they need to be invariant to permutations of the input set.

Depending on how they manipulate the point clouds, current point cloud based architectures can be split into three groups.

1. Direct Manipulation

Pointnet[30] developed by Qi et al was able to overcome this challenge on small sets of point clouds. By using point clouds as direct input into Recurrent Neural Networks[26] They were able to create a global point cloud signature that could classify and segment 3D objects in the point cloud. They further improved this model into Pointnet++[31] which recursively applied PointNet on nested partitions of the point clouds using a hierarchical neural network. In doing so they were able to capture the local structures of the point clouds as a result of their metric nature and thus achieve better performance than PointNet. For both of these publications, the source code was released for public use. Consequently, they have formed a fundamental foundation for further development of point cloud object detection methods.

2. Voxel Based

By dividing the pointclouds into 3D voxel grids, points within these voxels can be sampled to perform feature extraction. VoxelNet [42] is a state of the art architecture that uses this method to extract these features through Voxel Feature Extraction layer. The extracted features are then passed through a RPN to generate detections.

3. 2D-Based

This involves projecting the pointcloud into a 2D image plane coordinate system which can then be trained on existing image CNN models such as VGG-16. VeloFCN [] was one of the first methods to implement this approach using a fully convolutional network. However, VeloFCN did not include bird eye and front view representations.

Network Model	Mode	Code	Inference Time
VoxelNet	<i>LiDAR</i>	Unofficial	100ms
AVOD	<i>LiDAR+Image</i>	Yes	100ms
MV3D	<i>LiDAR+Image</i>	Unofficial	360ms
MONO3D	<i>Mono Image</i>	Yes	4.2s
3DOP	<i>Stereo Image</i>	Yes	3s

Table 21: Modes of Operation of Common Architectures

CHAPTER



IMPLEMENTATION

This chapter details the execution of the project.

3.1 Datasets

3.1.1 Context Classification

1. **CityScapes** - Cityscapes is a large-scale dataset used to develop pixel and instance level semantic segmentation models. It is composed of 29 scenes from 50 different cities captured using stereo cameras. In 5000 scenes, the images have been annotated on a pixel-level. 20000 scenes have also been coarsely annotated. In addition to this, a benchmark suite to evaluate these models is available.
2. **KITTI Object Detection**- The KITTI dataset was collected with the aim of encouraging the development of computer vision and robotic algorithms for AVs. The data was captured by a car fitted with a number of sensors including a high resolution greyscale and colour cameras, Velodyne HDL-64 LiDAR and a GPS/IMU inertial navigation system. The vehicle was driven around a city, rural areas and highways. This dataset is available as part of a benchmark suite for various AV object detection models.

3.1.2 Lidar Performance Evaluation

1. **University of Bristol Smart Internet Lab** - This dataset was captured from a Velodyne VLP-16 LiDAR on a stationary vehicle positioned at the Millennium Square in Bristol as part of the connected and autonomous vehicles project. Available as LiDAR network capture files(.pcap).

3.2 Can We Automatically Detect The Context in Driving Scenes?

Determining the context from images and point clouds where no prior information about their location nor context is provided is quite difficult. This is often the case in a lab setting where the data is obtained from public databases. Similarly, images and point clouds from the KITTI dataset did not have any such information. Consequently, creating a context detector that can be used in a lab setting would be very useful.

To begin with, I visually classified 3715 images from the KITTI dataset to be used as training and test data for the context detector. The context of the image scenes were determined using the following criteria. Urban regions were characterised by:

1. High density of road users often including pedestrians, cyclists and vehicles.
2. Presence of large multi-story buildings.
3. Presence of multiple transport facilities such as trams.

Non-urban regions were characterised by:

1. Low/medium density of road users mostly vehicles.
2. Few or no buildings.
3. Long stretches of motorways surrounded by vegetation.

Following this, the classified data was split on a 80:20 ratio to be used as the training and test set respectively.



Figure 31: Urban scene



Figure 32: Non-Urban scene

3.2.1 Image Context Detection

Images provide a rich representation of a scene that can be exploited through image segmentation. Various image segmentation models have been developed to break down images into coherent regions. Semantic segmentation involves classifying these regions into various classes on a pixel level. Classic computer vision techniques for semantic segmentation utilised Texton Forests[35] and Random Forest classifiers [34], however, deep learning techniques have overtaken them in terms of performance. Developed by Google, Deeplab-V3 is one of the best performing open-source models on the Cityscapes semantic segmentation benchmark table.

Classifying Semantic Histograms

Using the Deeplab-V3 network, I performed semantic segmentation on the classified images. For each image, I created a semantic histogram containing the number of pixels in each semantic class as seen in figure 33. By matching these histograms with the context label of the image, I was able to train a Support Vector Machine(SVM) to classify an image. Different linear and radial basis functions were tested on the SVM to see what function would perform best.

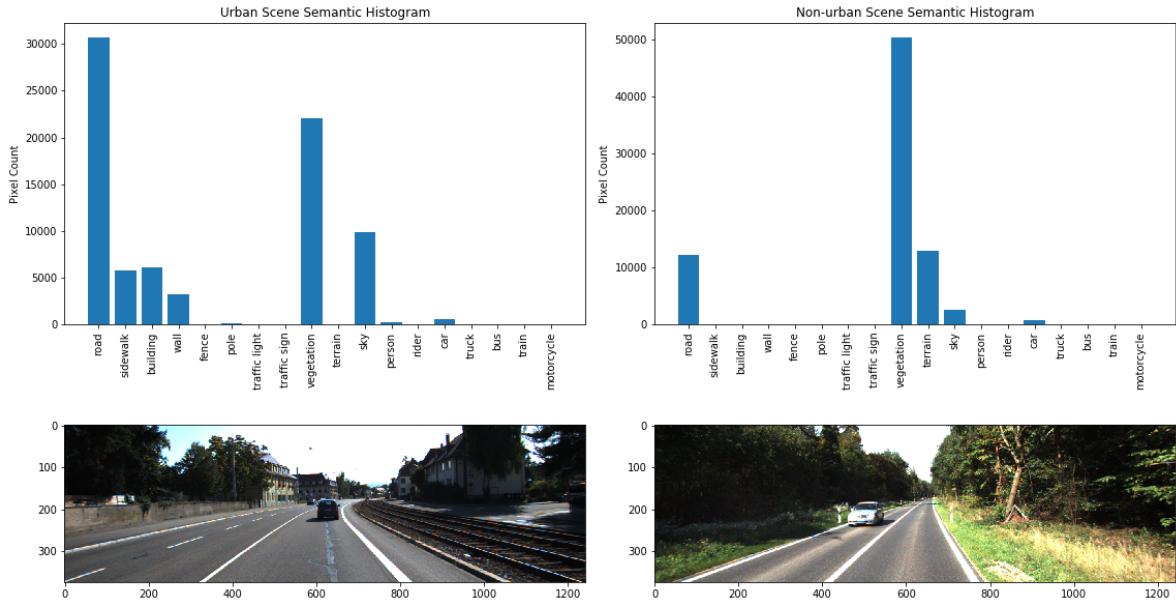


Figure 33: Semantic Histograms

3.2.2 PointCloud Context Detection

As compared to point clouds from RGB-D or stereo cameras, point clouds from LiDAR lack rich features. This is due to the sparse nature of the point clouds and as a result, the resulting representation tends to have a large number of 'holes'. Despite the availability of point clouds segmentation models, there are no datasets with annotations of outdoor scenes such as Cityscapes. As such using semantic histograms to characterise scene contexts in this case would not be suitable. A different approach was therefore used by first detecting the key points in the cloud, extracting and classifying features from them and later on matching these features in other point clouds.

1. Keypoint extraction

Similar to classic image processing, key points are salient points that are not affected by any form of transformation or distortion. As such, they are distinctive and repeatable in



Figure 34: Ambiguous scene

different points-of-view. Currently, only a few 3D keypoint detectors have been proposed. These include Intrinsic Shape Signatures(ISS)[], NARF[] and Uniform Sampling[] of point clouds in voxels(similar to VoxelNet's).

2. Feature description

Signature of Histogram of Orientations

3. Feature Matching

3.2.3 Implementation Issues

Despite being able to visually classify a large number of images, some images were difficult to classify as they exhibited characteristics from both contexts. Furthermore, due to the fact that the images was not contiguous , I was unable to infer their context by examining preceding image frames. As such, this affected the performance of both classifiers.

3.3 Do Some Object Detection Methods work better in Different Contexts?

Having been able to successfully classify and create a dataset of urban and non-urban images, the next step was evaluating how a LiDAR based and image+LiDAR based object detection model would perform in different contexts. For this task, the state-of-the-art VoxelNet(LiDAR only) and AVOD(LiDAR+image) proved to be the most suitable candidates. This was influenced by the fact that they both have similar inference times, and both were open-source with the only exception being that the VoxelNet implementation was unofficial¹. Both of these models were written in Python and run on the TensorFlow Deep Learning Framework.

3.3.1 VoxelNet

VoxelNet is an end to end point cloud based 3D object detection network that was released in November 2017 by leading researchers at Apple Inc. This network was one of the top performing LiDAR only models on the KITTI benchmark. However, the code was never released and only unofficial implementations are currently available online.

¹Had similar evaluation results as the unreleased original on KITTI benchmark.

3.3. DO SOME OBJECT DETECTION METHODS WORK BETTER IN DIFFERENT CONTEXTS?

3.3.1.1 Architecture Overview

VoxelNet is composed of three fundamental blocks.

1. Voxel Feature Encoding Layer

2. Convolutional Middle Layers

3. Region Proposal Network

3.3.1.2 Implementation Details

3.3.2 AVOD

3.3.2.1 Architecture Overview

3.3.2.2 Implementation Details

3.3.3 Evaluating with KITTI Dataset

3.3.4 Is VoxelNet Performance Valid for Different Datasets?

To validate the VoxelNet model, I used the Smart Internet Lab dataset that was obtained from a LiDAR positioned on a stationary car.

Preprocessing

Before using the data on VoxelNet, the data had to be preprocessed to the necessary input format. VoxelNet only required four input fields, **XYZ values** and **reflectance** of the points, whereas the dataset was in the form of network capture files(.pcap). To convert them into this format, I exported the capture file into CSV format for each of the frames. This was done in VeloView using the CSV export function. The result was a CSV file with 13 fields as seen in figure 35

Points_m_XYZ:0	Points_m_XYZ:1	Points_m_XYZ:2	X	Y	Z	intensity	laser_id	azimuth	distance_m	adjustedtime	timestamp	vertical_angle
0.01759156584739685	5.304835319519043	-1.421434164047241	0.01759156507648251	5.304835470033373	-1.421434195703044	1.0	0.0	19.0	5.492	343308097.0	343308097.0	-15.0
0.07194533199071884	20.6107349395752	0.3597639203071594	0.07194532898218986	20.61073481953913	0.3597639062981624	20.0	1.0	20.0	20.614	3433080900.0	3433080900.0	1.0
0.02194887027144432	5.988438129425049	-1.382549166679382	0.02194887062991644	5.98843819471877	-1.382549179997394	1.0	2.0	21.0	6.146	3433080902.0	3433080902.0	-13.0
0.02645202539861208	6.88900899887085	-1.33909749847412	0.02645202482367224	6.889008789131341	-1.339097529552591	1.0	4.0	22.0	7.018	3433080907.0	3433080907.0	-11.0
0.3046736121177673	75.89746856689453	6.64022159576416	0.3046736085365989	75.89747013826725	6.640221728458581	63.0	5.0	23.0	76.188	3433080909.0	3433080909.0	5.0
0.03370168805122375	8.045639038085938	-1.274315118789673	0.0337016894267474	8.045638637731509	-1.274315152217721	1.0	6.0	24.0	8.146	3433080911.0	3433080911.0	-9.0
0.3095385730266571	70.94056701660156	8.710489273071289	0.3095385870564042	70.94056833292017	8.71048945053951	63.0	7.0	25.0	71.474	3433080913.0	3433080913.0	7.0
0.04397721216082573	9.691121101379395	-1.18932227134705	0.043977212362424784	9.691120843322894	-1.18932326900786	1.0	8.0	26.0	9.764	3433080916.0	3433080916.0	-7.0
0.3213215470314026	70.80862426757812	11.2150993347168	0.3213215462835961	70.80862345723331	11.21509966766423	63.0	9.0	26.0	71.69200000000001	3433080918.0	3433080918.0	9.0
0.05691538738596306	12.07773017883301	-1.0566762685757976	0.0569153850187421	12.07773041569957	-1.05667625072606	3.0	10.0	27.0	12.124	3433080920.0	3433080920.0	-5.0
0.08184240758419037	16.16960144042969	-0.847423791885376	0.0818424105905633	16.16960230547166	-0.8474238034857464	2.0	12.0	29.0	16.192	3433080925.0	3433080925.0	-3.0

Figure 35: Smart Internet Lab Frame CSV

Out of the 13 fields, I extracted the XYZ values and intensity(reflectance) of the points and saved them as Numpy binary files. This resulted in a smaller file sizes(from around 4MB to 70KB) that are also quicker to read than normal CSV files.

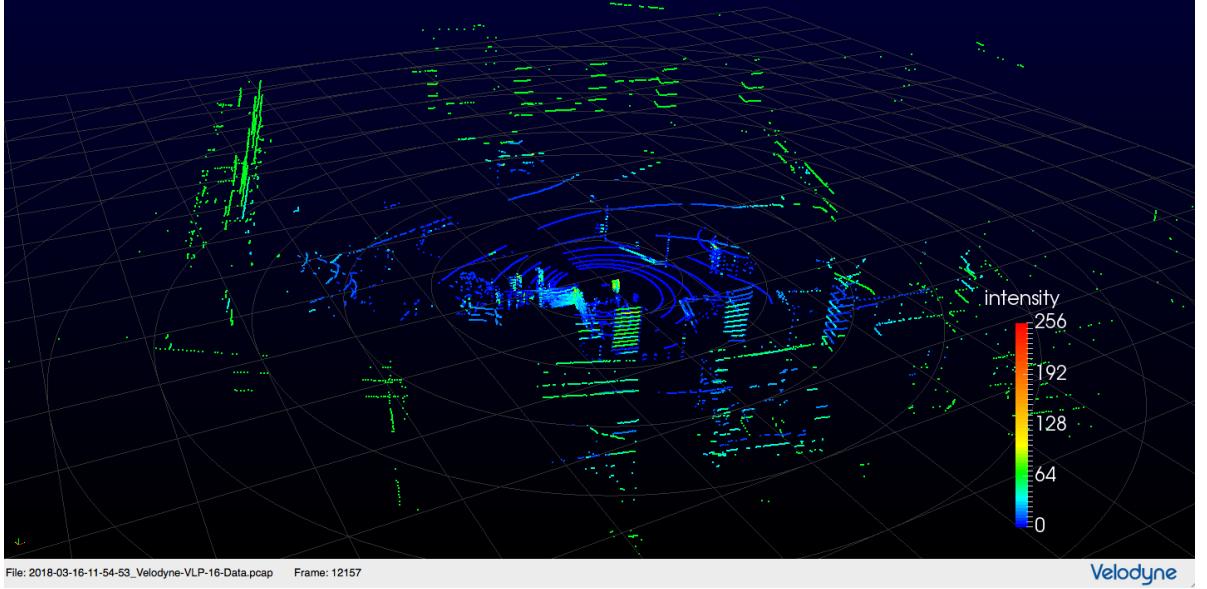


Figure 36: Veloview Frame of Smart Internet Lab data

Finally, I modified VoxelNet's configuration file to include the specifications for the VLP-16 LiDAR sensor. This was essential as the network was initially trained on KITTI point clouds that were obtained from a Velodyne HDL-64E with different specifications as seen in table 31. These specifications are necessary for manipulating the point clouds and therefore directly affect the performance of the network. The modified entries were the angular and vertical resolution, maximum and minimum XYZ values and the height of the VLP-16 LiDAR sensor on the vehicle. Given that there was no image data for visualisation, the image size in the configuration file was set to 0 to prevent unnecessary tensor memory allocation for images.

LiDAR	Hor FOV	Ver FOV	Range	Angular Resolution	Points/second	Channels
HDL-64E	360°	26.9°	120m	~0.4°	~2.2 Million	64
VLP-16	360°	± 15°	100m	0.1°	600,000	16

Table 31: Velodyne HDL-64E and VLP-16 Specifications.

Annotating Ground Truth Labels

The SIL dataset did not contain any ground truth labels for the point clouds as compared to the KITTI dataset. As a result, there was no metric to assess the performance of the network. To prevent this, objects from the dataset needed to be annotated to obtain some ground truth bounding boxes.

3.3. DO SOME OBJECT DETECTION METHODS WORK BETTER IN DIFFERENT CONTEXTS?

L-CAS Annotation Tool

Developed by the Lincoln Centre for Autonomous Systems Research, this tool provides a semi-automatic labelling function that clusters and highlight regions of interest that may contain objects. The user can then label them depending on the object class such as car, cyclist, pedestrian. The result is then stored in a file containing the objects and their positions in the point cloud. To use this tool, the .pcap capture files were converted into .pcd format using the ROS velodyne point cloud package².

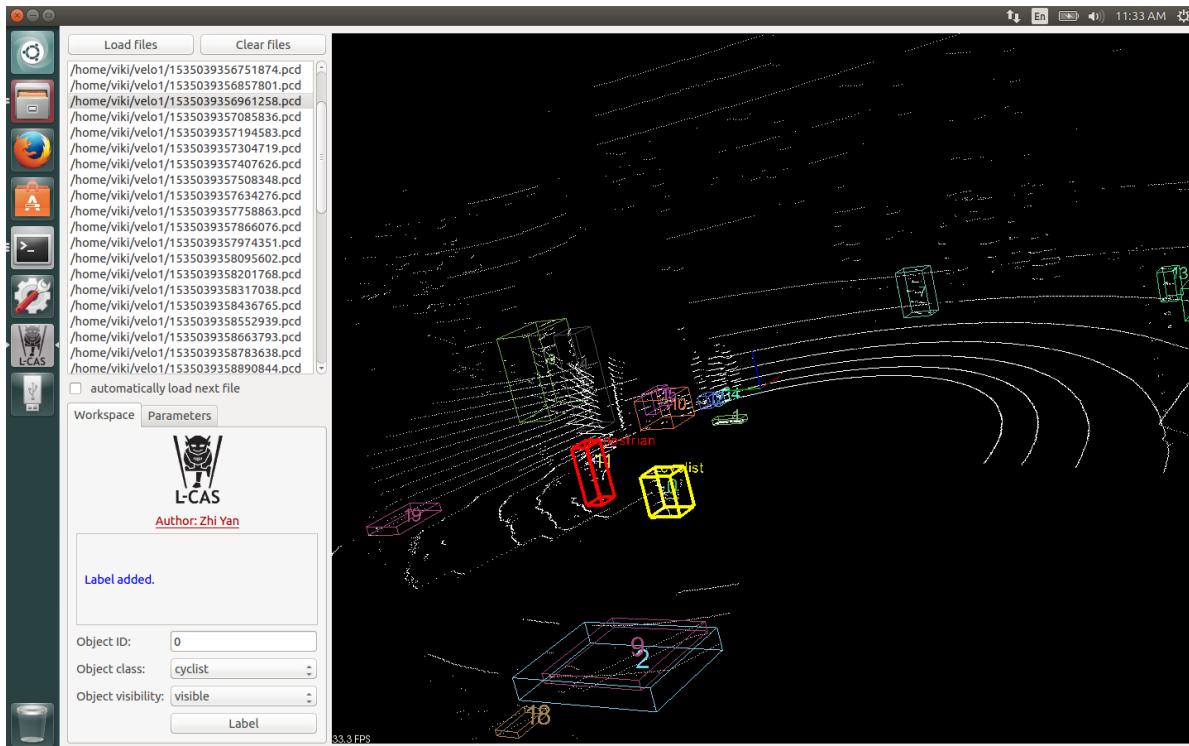


Figure 37: L-CAS Annotation Tool

²See listing A.1

RESULTS AND ANALYSIS

4.1 Context Detection Performance

4.1.0.1 Metrics

Context	Context Detection using PointCloud Feature Matching				Context Detection using Image Segmentation			
	precision	recall	f1-score	support	precision	recall	f1-score	support
<i>non-urban</i>	0.52	0.45	0.48	206	0.81	0.9	0.85	193
<i>urban</i>	0.51	0.58	0.55	206	0.9	0.81	0.85	218
avg / total	0.51	0.51	0.51	412	0.86	0.85	0.85	411

Table 41: Comparison of context detection methods

4.2 Model Performance

4.2.0.1 Metrics

For uniformity purposes, similar metrics to KITTIs evaluation protocol were used. However, as the annotations did not include the difficulty level, only the general performance was assessed.

4.2.0.2 GPU Statistics

During inference, statistics about the GPU was collected at an interval of 1 second using NVIDIAAs System Management Interval(nvidia-smi). The following metrics were collected.

- Power Draw
- Memory Used
- Temperature

- Clock Speed

Baseline

	Class	Car			Pedestrian		
Architecture	Difficulty	Easy	Medium	Hard	Easy	Medium	Hard
AVOD	2D Bounding Box	86.987999	77.10569	68.012459	56.214417	51.969517	46.578247
	BEV Bounding Box	86.00412	74.355942	65.62397	50.94368	49.857227	44.704525
	3D Bounding Box	75.447769	63.742085	54.334251	48.757492	44.84359	43.014023
VoxelNet	2D Bounding Box	65.951279	56.683437	55.972511	66.309807	60.556213	53.479141
	BEV Bounding Box	81.242409	70.672707	65.347595	50.308723	46.726196	41.24551
	3D Bounding Box	40.000149	34.892159	31.376112	34.161884	30.576441	28.982103

Table 42: My caption

Given that the data was collected from a stationary vehicle in an area with mostly pedestrians and cyclists, the dataset was evaluated on the pedestrian and cyclist classes only.

Context		Urban			Non-urban		
Difficulty		Easy	Medium	Hard	Easy	Medium	Hard
AVOD	2D Bounding Box	86.987999	77.10569	68.012459	89.186172	79.754562	78.550514
	BEV Bounding Box	86.00412	74.355942	65.62397	87.11274	76.859818	75.720955
	3D Bounding Box	75.447769	63.742085	54.334251	75.430656	64.199951	62.902302
VoxelNet	2D Bounding Box	69.597939	65.98201	59.284454	77.520409	67.733231	62.281651
	BEV Bounding Box	86.34037	76.187859	68.103294	88.635025	75.361214	69.502548
	3D Bounding Box	73.632263	58.473991	50.744587	68.620865	49.455608	45.809917

Table 43: Car Detection AP

Context	VoxelNet			AVOD		
	min	max	mean	min	max	mean
Urban	0.113	3.813	0.129	0.095	2.457	0.112
Non-urban	0.113	2.224	0.127	0.096	2.506	0.113

Table 44: Inference Time

C H A P T E R



FUTURE WORK

C H A P T E R



CONCLUSION



APPENDIX A

LiDAR	Hor FOV	Ver FOV	Range	Angular Resolution	Points/second	Channels
VLS-128	360°	+15°to -25°	300m	0.11°	~9.6 Million	128
HDL-64E	360°	26.9°	120m	~0.4°	~2.2 Million	64
HDL-32E	360°	+10°to -30°	80m-100m	0.1°	~1.39 Million	32
VLP-32C	360°	+15°to -25°	200m	0.1°	~1.2 Million	32
VLP-16	360°	± 15°	100m	0.1°	600,000	16

Table A1: Velodyne LiDAR Family

```

1 #Code to read .pcap files and convert them to .pcd
2
3 #Load existing pcap file and create a sensor publisher
4 $ roslaunch velodyne_pointcloud VLP-16-points.launch pcap:=(path to .pcap file)
5
6 #Receiver to convert sensor messages to .pcd (In separate terminal window)
7 $ rosrun pcl_ros pointcloud_to_pcd input:=/velodyne_points _prefix:=(path to save it)
8

```

Listing A.1: .pcap -> .pcd

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