Car Driving without Cameras

By

JONES MABEA AGWATA

Department of Computer Science
UNIVERSITY OF BRISTOL

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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.

The aim of this project is to replicate and improve on VoxelNet, A Region Proposal Network for point cloud object detection that was recently released by Apple Inc. Doing so will be of added value as the implementation is currently proprietary to Apple Inc. If successful, my implementation will be made open source and can be used for further research in the field of object detection from LiDAR point clouds. In addition, through the evaluation and analysis, I hope to propose ways in which my implementation can be used in making cheaper AVs through the use of solid-state LiDAR without having to use cameras at all.

In consideration of this, two main objectives emerge. The first is to develop a region proposal network for object detection from LiDAR point clouds. This will be implemented using the TensorFlow machine learning framework. The second will be a detailed evaluation report containing research into this topic area as well as an analysis and comparison of the performance of my implementation. Finally, an evaluation of the VoxelNet implementation will be performed to establish it's limitations and possible ways to improve it will be discussed.

This project will be 65% type I (Software Development) and 35% type II (Theoretical). Software development of the deep learning framework will involve obtaining AV videos and point cloud data from public datasets such as KITTI. This data will then be used in the development and training of the RPN. On completion of development, the model will be evaluated against the KITTI benchmark. Tentatively, datasets from the University of Bristol Robotics department from their AV project will be tested on the implementation and a sanitised LiDAR dataset released.

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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CHAPTER 1

INTRODUCTION

In the coming decade there is expected to be proliferation of new technologies that have been aided by recent developments in Artificial Intelligence (AI) and Machine Learning (ML). AI and ML have become topics of increasing interest in academic fields and industries globally. As a result, collaborations between these two fields has become increasingly common. With increase in computational power and the development of newer AI algorithms, robotic technologies have greatly advanced. They are now able to perform complex tasks that were once too difficult, dangerous or even impossible for humans to perform. Consequently, industries have benefited from the accuracy and efficiency provided by these robots.

An area that has developed a wide range of interest currently is the topic of autonomous vehicles. 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 as defined by the National Highway Traffic Safety Administration(NHTSA) depending on their level of autonomy.

- **Level 0** - No autonomy.
- **Level 1** - Basic driver assistance built into vehicle design.
- **Level 2** - Partially autonomous but driver expected to monitor environment at all times.

- **Level 3** - Conditionally autonomous with the driver not required to monitor the environment but is required to take back control if need be.

- **Level 4** - Highly autonomous with the vehicle capable of handling most conditions but the driver has the option to take control.

- **level 5** - Completely autonomous with the vehicle capable of handling all conditions.

The race to level 5 autonomous by different companies has seen major competition between these industry players. As such, they have invested heavily in designing and deploying AVs. However, these vehicles tend to have various sensors as seen in figure 2.2. These sensors are necessary for accurate navigation and safety. Nonetheless, they are quite expensive thereby making AVs not feasible at the moment.

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. Researchers working in these companies have released different papers proposing different options such as LiDAR only, camera and LiDAR or camera only configurations. However, the software implementations of these publications are often closed source including the datasets that they were tested on. As a result it is difficult for the academic community to replicate and validate the findings.

1.1 Aims and Objectives

Following the previous discussion, the aim of this project is to tackle the aforementioned issues by replicating VoxelNet, a region proposal network for point cloud object detection by Zhou et al [38]. In addition, we will open source this solution as well as the data sets used in order to make it reproducible. To achieve this aim, the following objectives will be undertaken:

1. Detailed analysis of state-of-the-art LiDAR-Based object detection deep neural networks.

2. Implement voxel feature encoding layer for grouping point clouds

3. Implement region proposal network for object detection.

4. Test and evaluate the implemented neural network against results of state-of-the-art point cloud object detection methods.

5. Propose improvements to expand benefits of our implementation.

6. Economic analysis of current implementations and our proposed improvements.

1.2 Deliverables

The deliverables are split into two groups.

- **End to end point cloud object detection RPN [30] .** This will be a software implementation of the system that will be publicly available through a Github repository.
- **Evaluation report.** In this report, the following topics will be discussed.
    1. A review of related research and implementations tackling object detection using LiDAR cloud points.
    2. Performance analysis of implementation and analysis criteria.
    3. A comparison between the implemented system and other state-of-the-art detection systems, potentially through a public benchmark.
    4. The ethical and safety implications of the system and its viability in a real world setting.
    5. Economic analysis of the implementation and its potential impact on the development of AVs.
    6. Validation of implementation performance against university or public datasets containing data from AVs.

1.3 Added Value

This project will implement and open source a sophisticated cloud point detection technique for use in autonomous vehicles. The implementation will be able to detect classes of objects such as cyclists, pedestrians and other vehicles on a real-time basis. In doing so, the project will democratize access to proprietary technology by Apple [38] to be used and developed further by future researchers working with object detection in point clouds. Following the detailed evaluation, I intend to propose ways through which this project can be implemented and improves with the aim of reducing the cost of AVs. This will be complemented further with an economic viability analysis to determine the effectiveness of the suggested approach. If successful, this project will provide a possible framework for the main stream adoption of AVs.

1.4 Research scope

The focus of this project is mainly with regard to computer vision, deep learning and robotics. Computer vision is the task of obtaining, processing, analysing and contextualising visual information to produce numerical information that can be understood and manipulated by computers. This is necessary in order to process and analyse the LiDAR data. Deep learning is a

broad term used to describe methods that utilise the use of deep neural networks that have a large number of layers. DNNs have become a heavily researched an invested area due to their ability to capture complex underlying models from data. This will be crucial for detecting objects from point clouds. This project will combine existing research using computer vision and deep learning such as [28][38] to develop a Region Proposal Network capable of accurately detecting objects in point clouds.

1.5 Report structure

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 and finally a brief overview of deep learning frameworks.

Chapter 3 is the final discussion that forms the conclusion of the review. In this chapter, I will evaluate what I hope to achieve and the assumptions and hypotheses that I have formulated.

CHAPTER 2

LITERATURE REVIEW

2.1 Components of an AV

Most self-driving cars consist of 4 main components:

- **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 2.1 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 LiDAR[1].

- **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 [15] 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 gryometers.

[1] See appendix A.2

Figure 2.1: Velodyne LiDAR family. From left: Velodyne HDL-64E , HDL-32E , PUCK

- **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 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)[33] or combinations with each other.

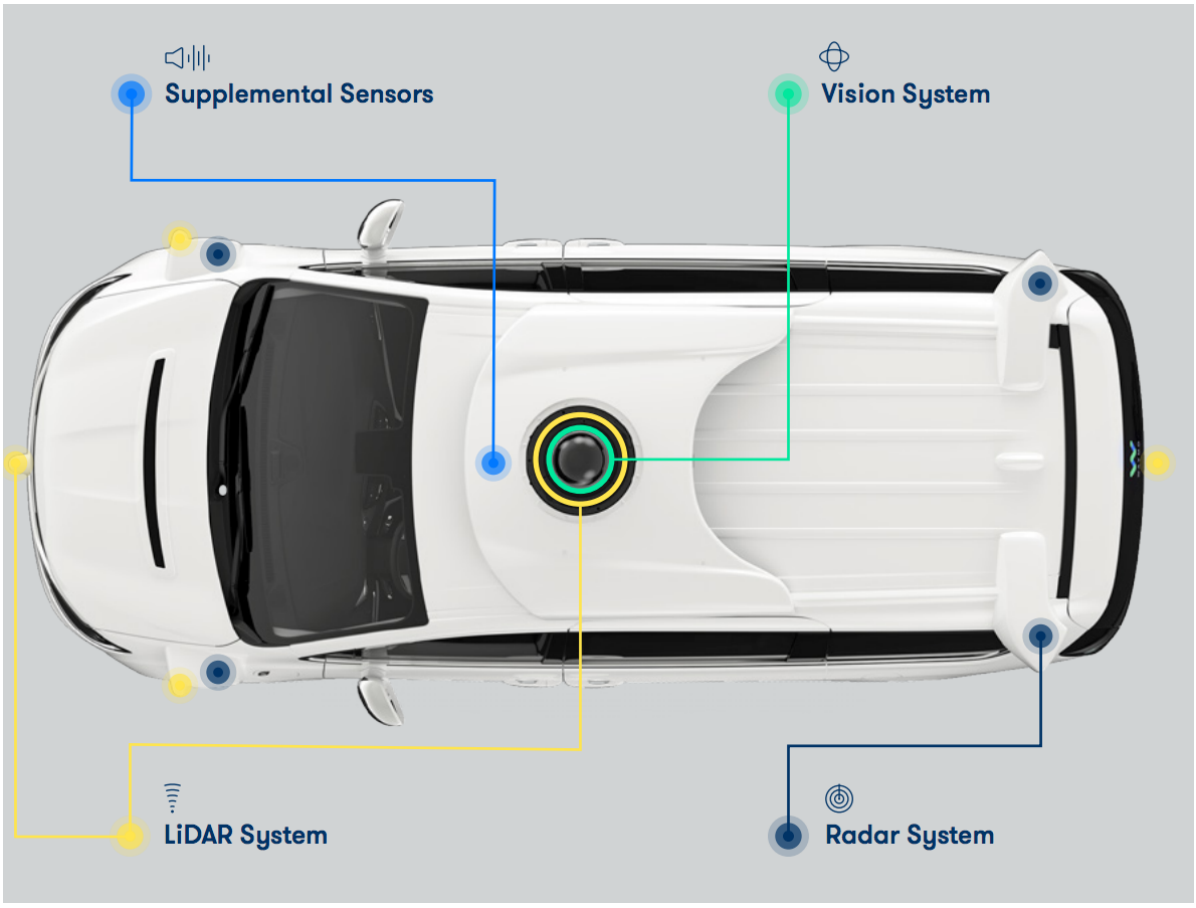


Figure 2.2: Components of Waymo's Self Driving Car [35]

2.2 Legal, Ethical and Economic Considerations

The classic ethical dilemma for self driving cars poses a scenario whereby AVs are presented with a situation whereby a fatal accident is inevitable. For example, the AV either has to crash into a group of people in order to save the life of a passenger or to crash itself and sacrifice the life of the passenger. This dilemma highlights important legal, ethical and economic considerations to be considered by companies involved in the production of AVs and their corresponding systems.

According to [11], there are no public laws that cover the use of independent autonomous vehicles in public spaces. In his article, he cites the fundamental issue as "understanding and accepting the effect of AVs as an independent action by a machine". Due to the lack of public laws on their use, he proposes extending fundamental rights such as the right to life into the framework for creating laws that cover emerging technologies that have an effect on the public, that are otherwise not accounted for in traditional laws.

Bearing this in mind, it is important to note that despite improvements in traffic safety over the years, 94% are still caused by human beings with a large majority of them being fatal with the current human error rate being 1 in 100 million miles. This creates a realistic baseline that can

then be extended in evaluating the performance of AV systems. As such, if the risk of automation is lesser than the risk of human vehicle control then the AV would be beneficial. Consequently, the AVs are not to be considered as perfect systems.

With regard to economic considerations, car manufacturers involved in the production of AVs have to ensure that their AVs are able to handle numerous scenarios even if they are rare or considered statistically impossible. They should also be required to take legal liability in case any of their system components are defective and result in failures or accidents. This is important for customer trust without which they will not be able to convince customers to shift to AVs. In addition, for the adoption of AVs to be widespread, they have to be reasonably priced and efficient. With the current prices of the the various components and their power consumption, the adoption of AVs at the moment is not viable.

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.

2.3 Industrial Approaches

In order to be viable, AVs need to meet a few constraints as discussed in [22].

- **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 [26], 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.

- **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

2.3.1 Camera

Mobileye[25], 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.[16]

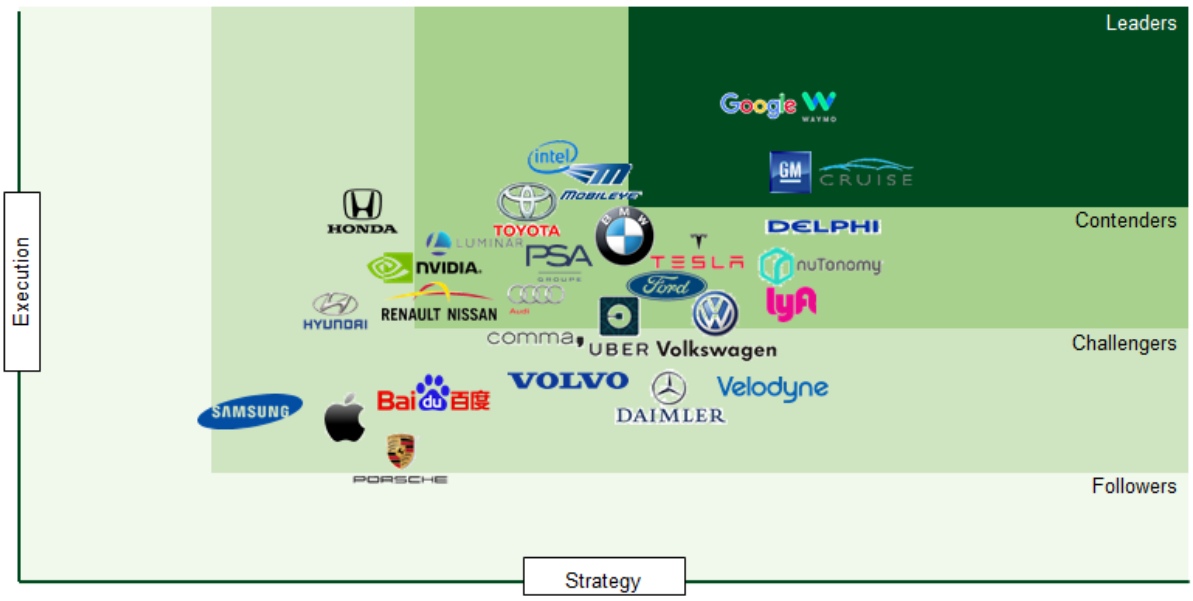


Figure 2.3: AV Leaderboard. Navigant Research[31]

2.3.2 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.

2.3.3 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. In addition due to the number of sensors, the cost of these AVs is quite high and therefore not economically feasible.

2.4 Related Research

2.4.1 Classic Computer Vision

With regard to perception, classic computer vision methods have advanced over the years from simple algorithms such as SIFT[23] 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)[9] or Haar Features[34] that were used in classifiers. However, these methods have been unreliably slow and not as accurate. In addition these features are only able to model 2D data and therefore when applied to 3D data such as point clouds they are unusable. Furthermore, these feature detectors have to be hand-crafted manually which is a tedious process. As a result, such classical methods can not be used in AVs as they are not as robust and accurate.

2.4.2 Deep Neural Networks

The emergence and development of Deep Neural Networks such as Convolutional Neural Networks (CNNs)[19] 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

Due to the high prices of LiDAR units, there were many attempts to develop detection methods that would use standard cameras that were cheap and readily available. Chen et al [7] of Baidu Inc. developed a 3D proposal method from monocular images that would then be used as input to CNNs. In this method, 2D objects were detected in the images and then extruded into 3D using class segmentation, instance level segmentation, shape, contextual features and location priors. This method was one of the best performing monocular object detection method according to the KITTI Benchmark. However, this method only performed well in well lit environments. It's performance declined greatly in dark scenes. In addition, due to the lack of depth information, the accuracy of the method is entirely dependent on the segmentation of detected 2D objects. Furthermore, the source code of this paper was never released thus making it difficult to validate the results with other datasets

Another attempt at developing lower cost detection systems was through the use of stereo cameras. This involved deploying and calibrating two cameras and through stereo matching and reprojection, a 3D image could be obtained that contains depth information. However as with monocular systems, they suffered the same issue of poor performance in dark scenes. In light of this, such methods would not be viable for use in AVs.

Multimodal

In an effort to improve the accuracy and robustness of AVs, multimodal methods were developed. This involves combining both LiDAR and camera or a camera and a range finder(RGB-D). Both

these configurations provide depth information in the form of point clouds. Chen et al further reiterated their monocular approach into MV3D[8] 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. Similarly as before, the source code was never released and therefore their results cannot be validated with other datasets.

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 DNNs as they need to be invariant to permutations of the input set.

Pointnet[28] 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[24] 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++[29] 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.

An attempt at detecting objects in point clouds from a LiDAR mounted in a vehicle was performed by [20]. In their work, they used a Fully Convolutional Network (FCN) to detect and localise objects in a point cloud as 3D bounding boxes. They were able to achieve this by discretising the point clouds into square grids represented by a 4D array containing the dimensions and a channel indicating if there was a point at that space in the grid. It performed significantly well in the KITTI benchmark. However, the source code was not released.

Finally, [38] were able to create a point cloud based 3D object detection network by adding a Voxel Feature Extraction layer before a RPN that was able to divide the point cloud into voxels that were used as input for the RPN. The published results were well above the state of the art LiDAR object detection methods. As is the case with other publications, the source code was not released and therefore cannot be validated.

2.5 Deep Learning Framework

As mentioned in the previous chapter one of the main deliverables will be an end to end RPN model for detecting objects in point clouds. In order to develop this I will make use of a deep learning framework. At the moment, there are various distributions of deep learning frameworks that are available for different programming languages. A few popular ones include:

Framework	Programming Language(s)
Tensorflow	Python, C++ , R
PyTorch	Python
Caffe	C, C++, Python, MATLAB
MXNet	Python, C++, R, Julia
Microsoft Cognitive Toolkit/CNTK	Python, C++

Table 2.1: Popular deep learning frameworks

2.5.1 TensorFlow CNN

I intend to use Tensorflow on Python to implement the RPN for the following reasons.

1. **Large support community**
2. **Quick prototypying**
3. **Well tested and reliable**
4. **Portable**

Figure 2.4 illustrates a simple CNN visualisation which forms a major part of the RPN model. A python implementation can be found in Appendix A.1

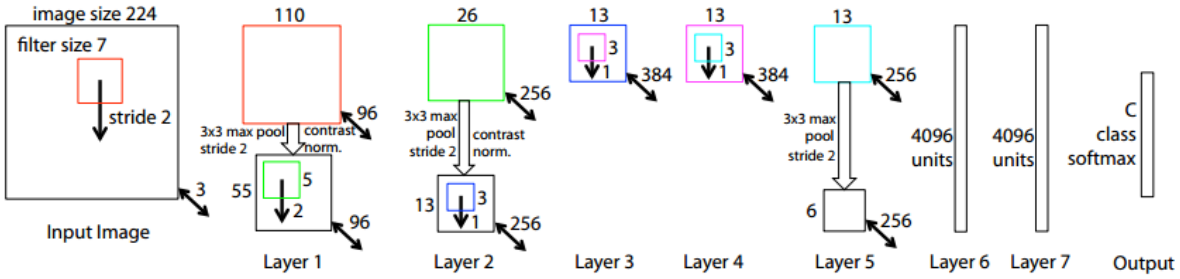


Figure 2.4: CNN Visualisation [37]

CHAPTER 3

PROJECT OUTLINE

3.1 Description of tasks

1. **Project environment setup**
   a) Download KITTI Dataset
   b) Split into training and test data
   c) Install Tensorflow and necessary libraries
   d) Review related implementations
2. **DNN implementation**
   a) Transform data into valid input
   b) Develop Voxel Feature Encoding Layer
   c) Develop CNN for object detection
   d) Integrate VFE and CNN layers
   Milestone: Prototype RPN model
   e) Add functionality for object classes
   f) RPN Training
   Milestone -Publish source code

   Deliverable -Robust and accurate object detection RPN.
3. **Testing and debugging**
   a) Initial testing

b) Initial debugging

c) Test added functionality

d) Debug added functionality

4. **Parameter tuning**

a) Compile parameters to test

b) Run model with parameters

c) Compile results

Milestone - Obtain best performing parameters

5. **Evaluation**

a) Obtain results of related implementations

b) Run benchmark tests

c) Compare results

6. **Validation with different datasets**

a) Download extra datasets

b) Split data into training and test data

c) Transform data into valid input

d) Evaluate model performance.

Deliverable - Performance analysis of model against different datasets.

7. **Report**

a) Write Up system design

b) Compile Evaluation results

c) Compile validation results

d) Analyse results

e) Editing and Formatting

Deliverable - Final thesis document.

8. **Poster**

a) Poster design

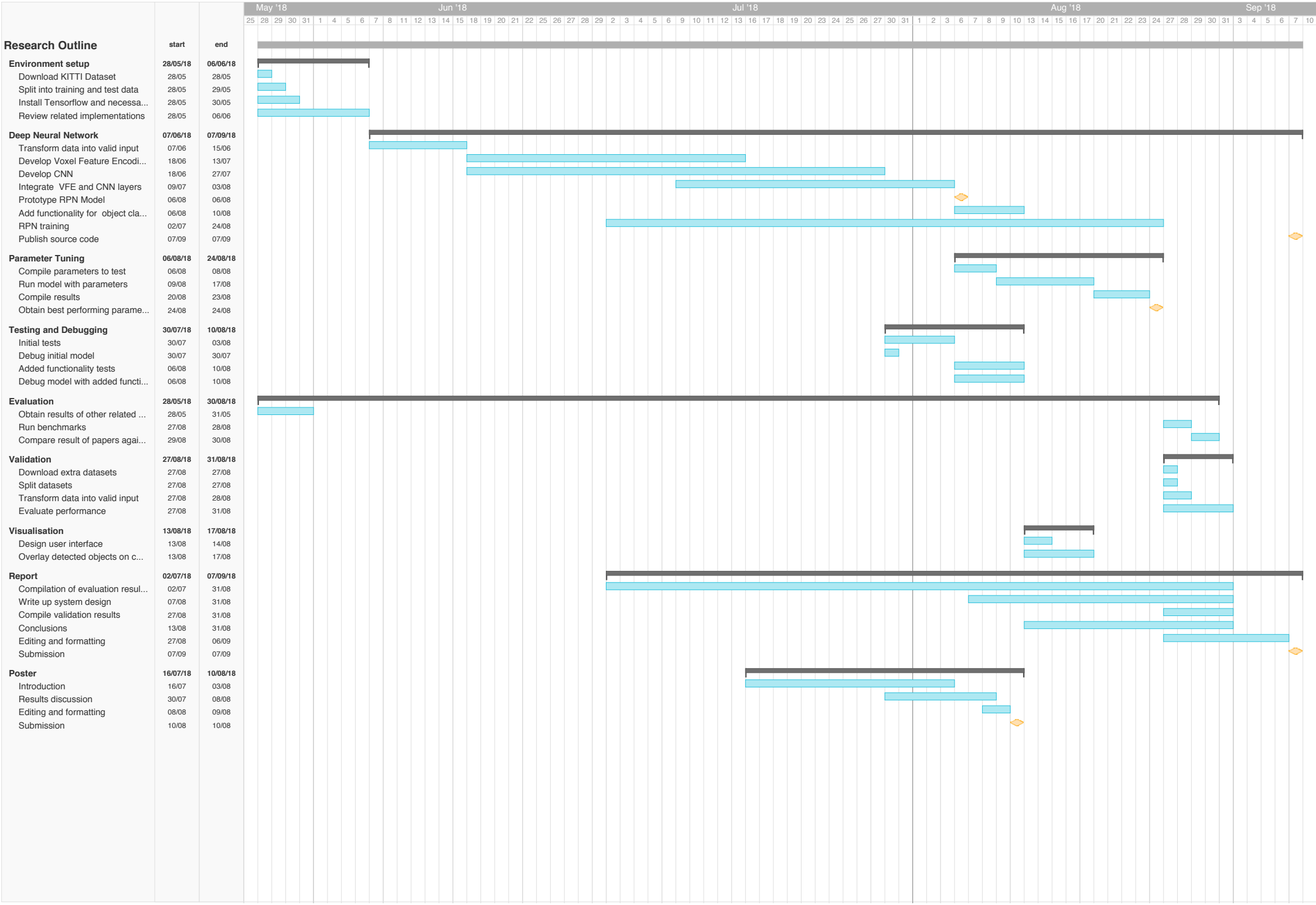
b) Editing and formatting

Deliverable - Final poster

3.2 Timeline and Risk Anaysis

Risk	Likelihood	Severity	Prevention	Contingency
Software Library incompatibility	4	2	Ensure necessary libraries and dependencies are installed beforehand	Use of ready instances on cloud platforms.
Loss of data	1	3	Frequent backups to GitHub and other local machines.	Datasets can be redownloaded from public websites.
Overestimated technical capability	3	2	Review related implementations and literature before beginning project	Large support community for Python and Tensorflow online and within university department.
Long GPU queue on Blue Crystal4	4	3	Queue work during low peak times	Use cloud instances for training

Table 3.1: Risk Analysis Table



Research Outline	start	end
Environment setup	**28/05/18**	**06/06/18**
Download KITTI Dataset	28/05	28/05
Split into training and test data	28/05	29/05
Install Tensorflow and necessa...	28/05	30/05
Review related implementations	28/05	06/06
Deep Neural Network	**07/06/18**	**07/09/18**
Transform data into valid input	07/06	15/06
Develop Voxel Feature Encodi...	18/06	13/07
Develop CNN	18/06	27/07
Integrate VFE and CNN layers	09/07	03/08
Prototype RPN Model	06/08	06/08
Add functionality for object cla...	06/08	10/08
RPN training	02/07	24/08
Publish source code	07/09	07/09
Parameter Tuning	**06/08/18**	**24/08/18**
Compile parameters to test	06/08	08/08
Run model with parameters	09/08	17/08
Compile results	20/08	23/08
Obtain best performing parame...	24/08	24/08
Testing and Debugging	**30/07/18**	**10/08/18**
Initial tests	30/07	03/08
Debug initial model	30/07	30/07
Added functionality tests	06/08	10/08
Debug model with added functi...	06/08	10/08
Evaluation	**28/05/18**	**30/08/18**
Obtain results of other related ...	28/05	31/05
Run benchmarks	27/08	28/08
Compare result of papers agai...	29/08	30/08
Validation	**27/08/18**	**31/08/18**
Download extra datasets	27/08	27/08
Split datasets	27/08	27/08
Transform data into valid input	27/08	28/08
Evaluate performance	27/08	31/08
Visualisation	**13/08/18**	**17/08/18**
Design user interface	13/08	14/08
Overlay detected objects on c...	13/08	17/08
Report	**02/07/18**	**07/09/18**
Compilation of evaluation resul...	02/07	31/08
Write up system design	07/08	31/08
Compile validation results	27/08	31/08
Conclusions	13/08	31/08
Editing and formatting	27/08	06/09
Submission	07/09	07/09
Poster	**16/07/18**	**10/08/18**
Introduction	16/07	03/08
Results discussion	30/07	08/08
Editing and formatting	08/08	09/08
Submission	10/08	10/08

CHAPTER 4

CONCLUSION

Following the discussions in the previous chapters, it is clear that there is lack of transparency between industry and academic research on AVs. This can be explained by the industrial competition with companies trying to establish themselves as the leaders in development of AVs. However, I believe that for expedited development of AVs there needs to be more collaboration between these two communities. This will provide an overall benefit as it will prompt the development of standards and regulations.

With regard to LiDAR-based object detection, new advances in solid state technology has allowed for the development of cheap LiDAR units such as Quanergy's 250$ unit. This presents an opportunity for AV manufucturers to switch to these cheaper units with no fear of losing accuracy. It is therefore my wish to implement my solution to be able to be used in solid-state LiDARs.

In pursuing this project, I intend to engage in an exploratory investigation in order to establish various options in the implementation of the various tasks listed in chapter 3. In doing so I will be able to provide an informed evaluation of the different factors affecting the development of AVs. Furthermore, if time allows, the issue of lack of interpretibility of deep ;earning models will be explored. Determinism of the AV systems is an important aspect in terms of safety.

APPENDIX A

A.1 CNN Example

```
def cnn_model_fn(features, labels, mode):
"""Model function for CNN."""
# Input Layer
input_layer = tf.reshape(features["x"], [-1, 28, 28, 1])

# Convolutional Layer #1
conv1 = tf.layers.conv2d(
inputs=input_layer,
filters=32,
kernel_size=[5, 5],
padding="same",
activation=tf.nn.relu)

# Pooling Layer #1
pool1 = tf.layers.max_pooling2d(inputs=conv1, pool_size=[2, 2], strides=2)

# Convolutional Layer #2 and Pooling Layer #2
conv2 = tf.layers.conv2d(
inputs=pool1,
filters=64,
kernel_size=[5, 5],
padding="same",
activation=tf.nn.relu)
pool2 = tf.layers.max_pooling2d(inputs=conv2, pool_size=[2, 2], strides=2)

# Dense Layer
```

```
pool2_flat = tf.reshape(pool2, [-1, 7 * 7 * 64])
dense = tf.layers.dense(inputs=pool2_flat, units=1024, activation=tf.nn.relu)
dropout = tf.layers.dropout(
inputs=dense, rate=0.4, training=mode == tf.estimator.ModeKeys.TRAIN)

# Logits Layer
logits = tf.layers.dense(inputs=dropout, units=10)

predictions = {
# Generate predictions (for PREDICT and EVAL mode)
"classes": tf.argmax(input=logits, axis=1),
# Add `softmax_tensor` to the graph. It is used for PREDICT and by the
# `logging_hook`.
"probabilities": tf.nn.softmax(logits, name="softmax_tensor")
}

if mode == tf.estimator.ModeKeys.PREDICT:
return tf.estimator.EstimatorSpec(mode=mode, predictions=predictions)

# Calculate Loss (for both TRAIN and EVAL modes)
loss = tf.losses.sparse_softmax_cross_entropy(labels=labels, logits=logits)

# Configure the Training Op (for TRAIN mode)
if mode == tf.estimator.ModeKeys.TRAIN:
optimizer = tf.train.GradientDescentOptimizer(learning_rate=0.001)
train_op = optimizer.minimize(
loss=loss,
global_step=tf.train.get_global_step())
return tf.estimator.EstimatorSpec(mode=mode, loss=loss, train_op=train_op)

# Add evaluation metrics (for EVAL mode)
eval_metric_ops = {
"accuracy": tf.metrics.accuracy(
labels=labels, predictions=predictions["classes"])}
return tf.estimator.EstimatorSpec(
mode=mode, loss=loss, eval_metric_ops=eval_metric_ops)
```

Listing A.1: Simple CNN implementation using Tensorflow in Python [1]

A.2 Types of LiDAR

- **Mechanical Mirror**
- **Solid State**
- **Optical Phase Array**
- **Microelectromechanical systems (MEMS)**

- **3D Flash**

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