CONCEPT DESIGN AND TESTING OF A GPS-LESS SYSTEM FOR AUTONOMOUS SHOVEL-TRUCK SPOTTING

by

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Abstract

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Haul truck drivers frequently have difficulties spotting beside shovels. This is typically a combination of reduced visibility and poor mining conditions. Based on first-hand data collected from the Goldstrike Open Pit, it was learned that, on average, 9% of all spotting actions required corrective movements to facilitate loading. This thesis investigates an automated solution to haul truck spotting that does not rely on the use of the satellite global positioning system (GPS), since GPS can perform unreliably. This thesis proposes that if spotting was automated, a significant decrease in cycle times could result.

Using conventional algorithms and techniques from the field of mobile robotics, vehicle pose estimation and control algorithms were designed to enable autonomous shovel-truck spotting. The developed algorithms were verified by using both simulation and field testing with real hardware. Tests were performed in analog conditions on an automation-ready Kubota RTV 900 utility truck. When initiated from a representative pose, the RTV successfully spotted to the desired location (within 1 m) in 95% of the conducted trials. The results demonstrate that the proposed approach is a strong candidate for an auto-spot system.

KEYWORDS: spotting time, pose estimation, mobile robotics, GPS, autonomous vehicles
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# Table of Contents

Abstract ................................................................................................................................. ii
Acknowledgements ................................................................................................................ iii
Nomenclature .......................................................................................................................... x

Chapter 1 Introduction .......................................................................................................... 1
  1.1 Motivation ........................................................................................................................... 1
    1.1.1 Automation in Mining ................................................................................................. 1
    1.1.2 Spotting Deficiency ................................................................................................. 4
    1.1.3 Clearpath Kubota RTV 900 & ROS Platform .......................................................... 5
  1.2 Problem Formulation ...................................................................................................... 6
  1.3 Scope of Work .................................................................................................................. 7

Chapter 2 Auto-Spot Investigation ....................................................................................... 8
  2.1 Nevada Research Trip ..................................................................................................... 8
    2.1.1 Equipment ................................................................................................................ 10
    2.1.2 Deployment .............................................................................................................. 11
    2.1.3 Analysis Method ..................................................................................................... 12
    2.1.4 Results .................................................................................................................... 13
  2.2 Mine Authority Insights ............................................................................................... 17
  2.3 Automation of Mining Equipment ............................................................................. 19
  2.4 Commercial Vehicle Automation ............................................................................. 22
  2.5 Sensor Options ............................................................................................................. 24

Chapter 3 Auto-Spot Design ............................................................................................... 26
  3.1 Introduction .................................................................................................................... 26
    3.1.1 Spotting Configurations ......................................................................................... 26
    3.1.2 System Configuration ............................................................................................. 29
  3.2 Auto-Spot Procedure .................................................................................................... 32
    3.2.1 Auto-Spotting Operational Concept ....................................................................... 32
    3.2.2 RTV Spotting Experiments .................................................................................... 35
    3.2.3 Optimal Loading Location ....................................................................................... 38
  3.3 Kinematic Vehicle Model ............................................................................................. 40
  3.4 Control Algorithms ....................................................................................................... 43
  3.5 Localization ................................................................................................................... 45
    3.5.1 Vehicle Pose Initialization ....................................................................................... 46
Honeywell SMART Position Sensor Linear Configuration ........................................ 96
Cherry Geartooth Speed Sensor ................................................................. 96
List of Figures

Figure 1: Average daily spotting times for 797 haul trucks at Syncrude open pit [1] .................. 3
Figure 2: Spot marker on a double-sided loading shovel [2]......................................................... 4
Figure 3: Clearpath Kubota RTV autonomous-ready utility vehicle ............................................. 6
Figure 4: Yearly average spot times for haul trucks at Goldstrike open pit [9]......................... 10
Figure 5:Parsed GPS trace data from a haul truck and shovel at Goldstrike............................. 13
Figure 6: Shovel-Truck spotting with a small corrective measure .............................................. 14
Figure 7: GPS trace data exhibiting a shovel-truck spot failure ............................................... 15
Figure 8: Schematic of the shovel & truck configuration during loading .................................. 16
Figure 9: Top view of vehicle determining acceptable parking bay [26]............................... 23
Figure 10: IPAS Assisted Parking System HUD within a Lexus Vehicle [27]............................ 24
Figure 11: Shovel-Truck schematic of a frontal cut with double-sided loading [12]............. 27
Figure 12: Shovel-Truck schematic of double-sided loading at a parallel cut [12]................. 28
Figure 13: Schematic of the shovel-truck Pre-Spot Zone ...................................................... 31
Figure 14: Kubota RTV acceptable spot angle within pre-spot zone ....................................... 32
Figure 15: Flowchart of operational procedures for the auto-spot system............................ 34
Figure 16: Network map between shovel and truck nodes....................................................... 36
Figure 17: Overhead view of the experimental setup for the auto-spot system.................... 37
Figure 18: Loading configuration of shovel and truck around shovel swing radius ......... 40
Figure 19: Kinematic model of Kubota RTV with positive reverse motion ............................ 41
Figure 20: Error states of Kubota RTV from desired spotting path........................................ 43
Figure 21: Simplified control diagram of simulator design at conception............................ 52
Figure 22: Auto-Spot block model phase development ....................................................... 54
Figure 23: Closed loop simulator design in MATLAB® Simulink® environment.................. 55
Figure 24: RTV simulating dead reckoning of state error..................................................... 56
Figure 25: Error analysis of EKF estimator using GPS ....................................................... 57
Figure 26: Effect of incorrect GPS signal to EKF estimator ................................................ 57
Figure 27: State estimation error during manual operation ................................................... 58
Figure 28: State estimation error during optimal spot routine .............................................. 59
Figure 29: State estimation error during typical spot routine .............................................. 60
Figure 30: Pre-Spot test locations schematic ..................................................................... 61
Figure 31: State estimation error with Θ initially greater than 30° from the desired path ...... 62
Figure 32: Kubota RTV with spotting hardware at Innovation Park testing facility ............ 65
Figure 33: ROS system map ................................................................. 68
Figure 34: Auto-Spot sequence visualized in RVIZ ........................................... 69
Figure 35: Hall effect sensor mounted to front axle measuring ticks from 80 spoke gear .......... 70
Figure 36: Auto-Spot state error of EKF estimator using GPS ........................................... 72
Figure 37: Error state plot from Pre-Spot Location #1 ........................................... 74
Figure 38: GPS signal roaming during spotting action from Pre-Spot Location #2 ............... 75
Figure 39: State error for auto-spot test outside pre-spot zone ........................................... 76
Figure 40: State error for auto-spot with higher resolution LiDAR ................................. 77
Figure 41: State error for auto-spot test outside pre-spot zone with higher resolution LiDAR .... 78
Figure 42: State error during steering encoder failure .................................................. 79
Figure 43: Data Sheet for Sick LMS 111 [44] .......................................................... 93
Figure 44: Expected error from Trimble AP10 GNSS-Inertial OEM System [45] ................. 94
Figure 45: Data Sheet for Trimble AP10 GNSS-Inertial OEM System [45] ......................... 94
Figure 46: Datasheet for ADIS 16362 IMU [46] .......................................................... 95
Figure 47: Data sheet for contactless absolute encoder made by Honeywell (SPS-HALS) [47] .... 96
Figure 48: Data sheet for magnetic sensor made by Cherry (GS100502) [48] ...................... 96
List of Tables

Table 1: Shovel-Truck location metrics calculated from GPS trace data................................. 16
Table 2: A comparison of shovel versus haul truck mounted LiDAR sensors ............................ 29
Table 3: Pre-Spotting test locations ......................................................................................... 66
Table 4: Final loading location error for UKF based auto-spotting design............................ 73
Nomenclature

dFace  The distance from shovel centre pin the mining face

dShovel  The average loading radius of the P&H 4100C

e_H  RTV heading error in relation to desired spotting path (rad)

\( \dot{e}_H \)  Change in heading error over time (rad/s)

e_L  RTV path error or distance of RTV from desired path (m)

\( \dot{e}_L \)  Change in path error over time (m/s)

EKF  Extended Kalman Filter

LiDAR  Laser Scanner (Sick LMS 111)

\( \mathbb{N} \)  Normally distributed with mean \( \bar{x} \) and covariance \( \sigma_x^2 \)

\( \omega \)  Vehicle rotational rate (rad)

\( P_{k^-} \)  Covariance matrix of pose estimate \( \hat{q}_{k^-} \)

\( P_{k^+} \)  Covariance matrix of pose estimate \( \hat{q}_{k^+} \)

Pre Spot Zone  The area in which a haul truck can stop and theoretically be safely controlled to the loading location

\( q \)  Locally aligned pose of RTV

\( \hat{q}_{k^-} \)  Estimate of pose \( q \) from prediction estimator
\( \hat{q}_k^+ \) Estimate of pose \( q \) from corrective estimator

\( Q_{en} \) Measurement noise of wheel encoders (m)

\( Q_{gyro} \) Measurement noise of gyroscope (rad/s)

\( Q_{steer} \) Measurement noise of steering encoders (rad/s)

\( \phi \) Steering angle measured by a contactless absolute encoder (rad)

\( R \) Process noise

\( R_{mult} \) Multiplier applied to \( R \) to balance estimations

ROS Robot Operating System running on Clearpath Kubota RTV

RTV Kubota RTV (Rugged Terrain Vehicle) vehicle testing platform

\( \dot{\theta} \) Rotational rate of the RTV measured by a gyroscope (rad/s)

\( \theta_p \) The angle between the excavation and loading vectors; effectively the swinging angle (rad)

UKF Unscented Kalman Filter

\( V \) Vehicle velocity (m/s)

\( z_k \) Array of range values measured by the LiDAR
Chapter 1

Introduction

1.1 Motivation

1.1.1 Automation in Mining

Simple operations are typically the first tasks to be automated in industrial applications since uncomplicated actions can be modelled and left to control systems to manage functionality. As systems become more complicated, the ability to model and control their underlying processes increases in complexity. A classic complication is the introduction of an uncertain environment that lacks infrastructure, such as is common at mine sites. This uncertainty makes it difficult for a freely moving device, such as a haul truck, to interact with other objects without location awareness. This is evident in open pit mining, where vehicles typically experience a low level of autonomy. If one were to search ‘Autonomy in Mining’ in an engineering library’s database or a search engine most of the articles found would be about autonomous data mining tools/methods. Searching autonomy in mineral extraction does not help; there is a definite lack of engineering investigation into this application area in comparison to what can be found about factory automation or the application of robotics in other industrial domains. This is surprising, considering the increasing demand for skilled labour, the advent of high precision GPS and robotic technologies, and ever-present incentives to increase profit margins. In the coming decades, we will see a slow yet inevitable movement towards automated equipment in mining environments.
One way of increasing profitability at a mining operation is to reduce haul truck cycle times. This increases overall efficiency, while at the same time increasing ore production. A portion of a haul truck’s cycle time can be spent spotting (strategically parking beside a shovel for effective loading). Haul truck drivers frequently have difficulties parking beside shovels, and at times must make multiple attempts. This is typically because of a combination of poor visibility and changing orientation of the shovel with respect to the working face. This means that it may require multiple attempts by the haul truck driver to successfully park beside the shovel. Figure 1 shows averaged daily cycle times for several shovels over the course of two months. Disregarding the extremes well over 100 seconds in June 2008, the graph shows some interesting results. The most notable result is that a reasonable spotting time for a haul truck is roughly 50 seconds, but can average as high as 100 seconds. This is a serious concern when one considers that a shovel will typically fill several hundred trucks in a day. This data was only used to establish whether there was apparent variability in spot times and wasn’t used to compare haul truck spotting times as reporting procedures vary between operations.
Figure 1: Average daily spotting times for 797 haul trucks at Syncrude open pit [1]
1.1.2 Spotting Deficiency

The Candidate travelled to Barrick Gold Corp.’s Goldstrike open pit mine in Elko, Nevada to observe and characterize current spotting standards (Section 2). Current spotting methods are rather rudimentary. When a shovel is loading from both sides, a marker is often attached to the rear end of a shovel to help indicate to a truck driver where an appropriate loading location might be (Figure 2). Also, while swinging, a shovel’s wide rear section poses a contact concern to haul trucks during spotting and loading.

![Spot Marker on a double-sided loading shovel](image)

Figure 2: Spot marker on a double-sided loading shovel [2]

Often haul trucks will back up too far and run their tires into the working face. This can cause tire wear and premature failure. Haul truck tire cost is a concern for any mining operation but quite significant for operations with Caterpillar 797/Komatsu 960 fleets. Each truck requires six tires at a cost of approximately $50,000 US each [3]. Tire cost is significant because of the specific tire required by the large haul trucks. Under normal conditions, the tires last approximately 6000 hours (roughly eight months of operation) depending on surface conditions [4]. This means that
in a given year, a typical heavy hauler will go through 1.6 sets of tires at a cost of approximately $450,000 US. While this approximation will vary from site to site, it illustrates that minimizing tire wear and strain are significant objectives for mining operations to reduce operating costs.

Although the above-mentioned concepts are pivotal to the improvement of mining practices, perhaps the most important enhancement will be in safety. Robotic spotting systems would minimize potential for physical interaction between haul trucks and shovels. Often a shovel dipper (bucket) and the haul truck bed impact each other due to human error. This is a serious safety concern, as well as a maintenance issue, that could be reduced through an automated spotting system.

1.1.3 Clearpath Kubota RTV 900 & ROS Platform

The subject of this thesis was also partially motivated by the availability of unique equipment at Queen’s University. Through a Canadian Foundation for Innovation (CFI) grant and partner contributions, the Mining Systems Laboratory (MSL) contracted Clearpath Robotics to design and build two autonomous vehicle test beds; one based on a Kubota RTV 900W diesel utility vehicle and the other based on a Kubota R520S wheel loader. The RTV is pictured in Figure 3. The goal of this purchase was to generate a testing platform that would “support research into the development of navigation, control and process optimization system for next-generation mobile mining equipment” [5]. The robots are fitted with a suite of sensors and servo controllers to allow for the testing of autonomous systems, making them automation-ready. Clearpath’s design uses the Robot Operating System (ROS) infrastructure to handle the higher-level functionality. For example, through ROS, commands can be sent to the throttle, brake and steering controllers [6]. ROS also handles the sensor input/output and data logging. ROS’s mission is to “… provide libraries and tools to help software developers create robot applications” [7]. ROS is open source
reusable software developed by Willow Garage with help from the robotics community. Clearpath’s work and the ROS system were vital to the completion of this research.

Figure 3: Clearpath Kubota RTV autonomous-ready utility vehicle

1.2 Problem Formulation

As discussed above, haul truck operators in open pit mines often have difficulties spotting their vehicles to an appropriate loading position. Several research questions were initially identified to guide the progress of the research presented in this thesis.

1. Could an autonomous spotting system decrease spotting times and incidents of vehicle collisions? Assuming this is so, what is the optimal haul truck loading position? Does this vary depending on loading configuration?
2. How to define or measure the optimal loading position? What are the most appropriate and practical sensors for measuring this?

3. What would an autonomous spotting system look like? What vehicle control and navigation algorithms must be designed, employed, or adapted to suit this problem?

1.3 Scope of Work

The scope of work for this thesis includes the following:

- An investigation into current auto-spotting technologies, including a report on a field expedition to collect data, insights from mine authorities, and the current state of automation for haul truck and other commercial vehicles.

- A proposed automated spotting system design concept, including algorithm development, localization methods, and vehicle control functions to auto-spot a haul truck-like vehicle with a focus on GPS-less solutions.

- The development of a simulator to test the spotting system design. This includes simulating vehicular kinematics as well as the employed sensing instruments. The simulator was developed in MATLAB® and then later ‘ported’ into ROS to facilitate development on the Kubota RTV.

- The development of the Kubota RTV mine vehicle testing platform, which involved many complications and reported learning experiences.

- The results of auto-spotting tests, including performance, conducted with the RTV.

- Discussions about the future steps necessary to implement a full-scale working system in a mining environment, such as at Goldstrike open pit mine.
Chapter 2

Auto-Spot Investigation

2.1 Nevada Research Trip

In June of 2011, the candidate travelled to Elko, Nevada to collect spotting data at Barrick Gold Corporation’s Goldstrike open pit mine. The Goldstike pit is the largest of several gold mines located on the Carlin Trend in north-eastern Nevada [8]. Goldstrike is a conventional truck-and-shovel operation. Many different types of equipment are required to facilitate this style of operation. Large drill rigs bore blast holes that are then loaded with explosives and detonated to produce fragmented rock. Electric cable shovels then load large haul trucks with the blasted rock. The haul trucks transport the material to a variety of dump locations; ore is sent to a crusher or is stockpiled by grade, waste is sent to a dump site.

The revenue of a mine is directly affected by ore production (tonnes of material per unit time). As the carrying capacity of a haul truck is fixed, the load per cycle stays relatively static. This means each haul truck’s efficiency is predominately weighted on its cycle time, the time in which it takes for the vehicle to traverse from a shovel to a dump location and return back to the shovel. As a result, mine management place great emphasis on reducing cycle times. Cycle times are broken down into several components. The major categories are: hauling, queuing, spotting, loading, dumping and standby.

Maximizing revenues are as important as minimizing operational costs. A large cost incurred by a mining operation is the employment of their skilled labour force. Reducing the need for on-site
skilled labour, through autonomous applications, could reduce a mine’s operational costs. The lack of available skilled labour is an increasing concern to remote mining locations.

The research field trip’s goal was to observe current shovel-truck spotting procedures in an attempt to define the benefit of an autonomous spotting system. GPS data was collected in order to define shovel-truck characteristics such as:

- Optimal loading location and orientation with respect to shovel location and orientation
- Frequency of truck spotting failures
- Frequency of truck spotting events requiring corrective measures

The initial plan focused on interfacing with the mine site’s dispatch system to collect GPS trace data from haul trucks and cable shovels. Cable shovel data were also desired in order to analyze vehicle orientations and locations during spotting actions. The Modular Mining Systems (MMS) Ltd dispatch system at Goldstrike collects and logs a vast collection of data in order for mining authorities to analyze operational performance. This research focused on haul truck spotting times and their respective GPS data during spotting. GPS receivers, at a minimum, sample latitudinal and longitudinal co-ordinates. High precision GPS systems sometimes feature a second antenna that can facilitate the collection of vehicle heading data. At the Goldstrike Mine, shovels carried high precision units while haul trucks carried low precision. It was determined that this setup would be sufficient for capturing the desired GPS trace data.

Historical annual average cycle time data were collected from Goldstrike’s dispatch logs. The spot times were parsed from this data set and are plotted in Figure 4. One can see that the baseline spot time is roughly 70 seconds and varies upwards to 85 seconds. Considering that these values
are yearly averages, this represents considerable variation. Spotting times are logged using the shovel status at Goldstrike. The shovel operator toggles between various activities (loading, cleaning, standby, etc) so that equipment status times can be determined, such as spotting.

![Yearly Average Spot Times for Haul Trucks at Goldstrike Open Pit](image)

Figure 4: Yearly average spot times for haul trucks at Goldstrike open pit [9]

### 2.1.1 Equipment

One major concern with using the Goldstrike dispatch data was logging rates. Dispatch systems are typically not set to sample at rates that would best accommodate this project (1-5 Hz). Higher sampling rates were desired to accurately assess vehicle paths during the spotting process. As a back-up measure, additional standalone GPS receiver/loggers were purchased. They also served as a check on the data logged by the dispatch system. This decision was critical because Goldstrike’s dispatch system was unable to log data at a sufficient rate (<30 s). This was due to network traffic saturation. The additional GPS units purchased were five Qstarz BT-Q1000 XT GPS loggers due to their high sample rate, durability, portability, storage capacity and long battery life. Each unit was capable of recording at 1 or 5 Hz to a capacity of roughly 50,000 data points.
points per charge (e.g., 6 hours at 5 Hz). Chapman [10] also used the Qstarz GPS units in his study of haul time variability.

2.1.2 Deployment
The units were small and portable enough to easily deploy on haul trucks and shovels. To aid in analysis, the GPS units were mounted on the same style of haul truck (Caterpillar 797 Heavy Hauler) and shovel (P&H 4100C). Due to the standalone design of the units, each deployment had to be done manually to facilitate a dump of the collected data and to charge the data loggers. The units were mounted during shift changes at staging areas so that equipment availability was not impacted. They were fastened to the centre of the front guardrail on haul trucks and the back most corners on shovels to ensure optimal GPS reception. Two units were placed on shovels in order to determine vehicle and boom orientation. Careful planning had to be taken to ensure GPS units were deployed on haul trucks and shovels that would maximize vehicle interaction.

Mining dispatch systems use algorithms to minimize cycle times by coordinating shovel load and dump locations, hauling routes and a variety of other elements. Chapman outlines these elements quite well in Chapter 2 of his assessment of mine dispatch systems [10]. Because the vehicle allocations are determined by computer-based algorithms, a haul truck will not necessarily be loaded by the same shovel on each cycle. Measures, such as interfacing with the dispatch operators, were taken to maximize the number of visible shovel-truck spotting actions. The standalone units were deployed as often as possible on different haul trucks in order to obtain a representative sample of spotting data at Goldstrike mine. It is important to note that, while a significant amount of data was collected, the sample set is quite discontinuous. Deficiencies in this data include: recording only during dry summer months, spans a time period of only two months, and it pertains to only one type of shovel and truck.
2.1.3 Analysis Method

The resulting data was analyzed in MATLAB® version R2010b [11]. Multiple steps were taken to parse the GPS trace data into usable bins or ‘snapshots’. Each snapshot would be examined to determine the final loading location and whether the haul truck had to adjust its location in order to facilitate loading. These steps are outlined below:

1. Import raw data into MATLAB®, and store into arrays.

2. Parse raw data based on pit boundaries. As a haul truck enters the pit, a bin is initialized, as it exits, it is finalized. Pit boundaries were based on user-inputted polygons. An example of the result can be seen in Figure 5. The long swooping line represents the GPS trace of the haul truck. The cluster of crescents represents the GPS antennas mounted on the back corners of the shovel.

3. Based on GPS traces, each snapshot was individually analyzed to determine the relative GPS loading location. This was done by comparing the loading location of the haul truck in relation to the centre of axis of the shovel and a relative vector of the known mining face. The results are presented in Section 2.1.4.

It is important to note that while the analysis garnered interesting results, there was heavy reliance on user input for data sorting, as mentioned above. For this reason, contact was also made with various mining authorities to ascertain their thoughts on spotting deficiencies. Their comments can be found in Section 2.2.
2.1.4 Results

The results of parsing the GPS trace data are 267 recorded shovel-truck spots. Of the 267 interactions, 180 interactions were of sufficient quality and resolution, similar to the example presented in Figure 5. Visual assessment by the candidate concluded that 17 (9.4%) of the shovel-truck spots required corrective measures. A corrective measure was defined as any additional movement taken by the haul truck driver in order to facilitate loading. An example can be seen in Figure 6. These corrective measures can be required for a variety of reasons; e.g., being too far/close to the shovel or working face, the orientation of the truck bed not facilitating loading, or the haul truck having poor footing. Poor visibility is typically at the root of these problems. If a haul truck operator had a better perspective of where his/her vehicle was located, many of these issues could be mitigated. A heads-up-display (HUD) that gave an operator relative position to
the shovel could, arguably, help to improve spotting performance. However, mining authorities might also argue that the last thing equipment operators need is another HUD.

Figure 6: Shovel-Truck spotting with a small corrective measure

Of the 17 corrective measures, 4 (2.2%) were considered to be spotting failures. A spotting failure was characterized as the haul truck operator having to pull out of the loading zone in order to reset the spotting operation. This can be seen in Figure 7. From the Figure, one can see that the operator initially spotted too far from the shovel. The operator would have determined this from a visual assessment or the shovel operator may have informed them. As a result, the haul truck operator pulled out of the loading zone to move the haul truck closer to the shovel. These types of actions add to haul truck cycle times and thus decrease overall mine efficiency.
Another factor to consider in this situation is safety. In the case of Figure 7, the haul truck operator spotted too far from the shovel. A worst-case scenario would involve the opposite; the operator spotting too close to the shovel and incurring an equipment contact incident. Equipment contact incidents are a serious concern to mining authorities with respect to operator safety and equipment maintenance costs.

When a shovel is loading from both sides in this configuration, it affords haul truck operators a great deal of freedom of motion in choosing to their loading position. Excluding cut configurations that do not require truck spotting; a frontal cut is a highly efficient loading operation from the shovel operator’s perspective [12]. The effect of shovel configuration is discussed further in Section 4.1.1. From the snapshots, average dShovel and dFace values (Figure 8) were determined. dFace was measured as the distance from the loading location to a line

Figure 7: GPS trace data exhibiting a shovel-truck spot failure
parallel to the outer points of the shovel swing traces. The parallel line was set 22 m (shovel swing radius) from the shovel centre. dShovel was measured as the distance from the loading location to the centre of the shovel swing traces.

![Diagram of shovel and truck configuration](image)

**Figure 8:** Schematic of the shovel & truck configuration during loading

The determined means are characteristic of a straight cut configuration as the swing radius of the P&H 4100C shovel is approximately 22 m [13]. The calculated variance is also within reason. The interesting metric from this analysis is the variance in distance from the haul truck centre of bed to the digging face. This variability demonstrates the difficulty haul truck drivers have when gauging spotting distance. Another explanation could be differences of opinion between where haul truck and shovel operators assume the proper loading position is located. While shovel distance is constrained by swing radius, a suitable dFace distance could be set by sensing the distance to the bench.

<table>
<thead>
<tr>
<th></th>
<th>Mean (m)</th>
<th>Variance ($\sigma^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>dShovel</strong></td>
<td>21.57</td>
<td>3.01</td>
</tr>
<tr>
<td><strong>dFace</strong></td>
<td>22.85</td>
<td>13.25</td>
</tr>
</tbody>
</table>

Table 1: Shovel-Truck location metrics calculated from GPS trace data
2.2 Mine Authority Insights

There is very little literature on the subject of shovel-truck spotting. Therefore, contact was made with several industry representatives in order to gain perspective on spotting issues. Andrew Scott, Director of Mining Information Technology and Automation at Barrick Gold Corporation had this to say:

"I have had many chats with Mine General Managers and Mining managers and everyone says Spotting is a problem, not for the ‘A’ team, but for the B, C, D, E and F teams that we usually have on many mine sites. Any collision between truck and shovel is a cost (sometimes involving fire suppression system resets - approx 10K) .... Part of the my motivation (for auto-spot solutions) is that I see this as a step towards operator assisted driving leading to tele-remote operation of trucks which could lead to semi-Autonomous / Tele-remote operation/supervision to full autonomous / remote supervision capability for high altitude / difficult environments“ [14].

Peter Cunningham, Manager of Enterprise Realtime systems at Teck Resources Limited reiterated Scott's comments:

"A technology that would allow a truck operator to get into optimal position 2 seconds faster under all weather conditions would pay for itself. Note that a few times a year a haul truck accidentally contacts the shovel. This represents a further opportunity“ [15].

Though he has his doubts towards visible light sensors:

"A concern that I have with any technology that relies on visible light is that it may not be effective in heavy fog or snow. For that reason I believe the best core technology would be based on sub-light frequencies: radar, millimeter imaging, ultra-sound.”

His concerns certainly have merit; mining equipment can experience exceptionally adverse weather conditions. These conditions and their effect on an autonomous spotting system are discussed later in the text. Mark Richards, Manager of Mining Technology also with Teck adds to Cunningham's comments:
"Further to Peter’s email, most of our mines are not fully exploiting the double sided loading opportunities due to operator reluctance or safety concerns. There is considerable interest from all our operations in reducing delays at shovels while at the same time improving safety” [16].

Richards mentions operator reluctance to operate with double sided loading. There are significant safety concerns in relation to this technique. It requires multiple machines to operate in close proximity, and can be quite difficult for inexperienced operators. An autonomous or assisted spotting system would greatly benefit this situation. Increasing the use of double-sided loading has a significant impact on shovel efficiency.

Following the data collection expedition at Goldstrike open pit and subsequent conversations with representatives from Barrick Gold Inc. and Teck, the notion of a GPS-less solution was founded. Concerns regarding the accuracy of a GPS centric system were based on previously attempted implementations with less than favourable results.

Several shovel operators were interviewed at Barrick Goldstrike by the candidate while on the research expedition [17]. Some of the excerpts from the interviews and how they are relevant to the research presented in this thesis are outlined below.

1. What do you think is the biggest problem concerning spotting of haul trucks?

   “Inexperienced drivers having a hard time gauging distance from the face and the shovel. Over time this gets weeded out by the shovel operator correcting the truck drivers.”

2. How often do operators have to correct their spot? What usually causes it?

   “I see several resets in a day; this is usually because the operator feels his truck angle is too off for the shovel operator to get the bucket lined up with the bed.”
3. Does the orientation of the pit face and the shovel tracks have a large effect on where an operator will park?

“Sometimes, the tracks typically don’t have a large effect; they should be pointed towards the face anyways. We typically do a double-sided load if the advance allows it, the shovel is then accompanied by a dozer that cleans up the face. Sometimes when the bench they’re excavating isn’t lined up with the haul road, it can confuse the truck operator the first time they come to it. The guys often pick up habits from the driver that loads before them.”

The operators mention many of the issues addressed in the previous section; e.g., troubles gauging distances, orientation conflicts, and confusion due to the complexity of the system. An additional insight is the mention of operator behaviour. This concept will not be addressed at any length in this text as it falls outside the scope of this research project. It is worth mentioning that if haul trucks were autonomously controlled, this would greatly assist the study of vehicle interaction as it would result in more consistent behaviour.

As one can see, spotting deficiency is identified as a concern by mining authorities who operate equipment within the mine and develop its operational practices.

### 2.3 Automation of Mining Equipment

Equipment suppliers have been the primary investors in surface automation technology. “Mining companies have so far taken adaptor strategies where they let the supplier bear all the cost and risk of technology development” [18]. Mining companies tend to perceive the equipment supplier with the most sophisticated technology as the ‘best’ or most experienced equipment supplier, though they do not necessarily buy the automated equipment. This prompts equipment suppliers to innovate and, for example, automate their equipment. However, the mining industry likes to rely on traditional methods unless a new technology has been demonstrated successfully
elsewhere; i.e., in general, they tend to not be pioneers in technology. This is unfortunate because most profitable companies in other industries have relied heavily on technological innovations in order to stay competitive or gain competitive advantage. It is the candidate’s view that the mining industry will soon have to adopt these types of strategies more frequently, as many of the high-grade low-cost mines are beginning to go offline. Many of the major mines coming online in the next decade have considerable operating costs and could utilize automated machinery to significantly reduce operating costs [19].

Current automation methods employed by the major suppliers are unclear. This is most likely because equipment manufacturers wish to protect their trade secrets. Komatsu has this to say about their Autonomous Haulage System:

“Autonomous Haulage System (AHS) is a comprehensive fleet management system for mines. The dump trucks, which are equipped with vehicle controllers, a high-precision global positioning system (GPS), an obstacle detection system and a wireless network system jointly developed by Komatsu Ltd., Komatsu America Corp. and Modular Mining Systems, Inc., are operated and controlled via a supervisory computer, enabling them to be unmanned. Information on target course and speed is sent wirelessly from the supervisory computer to the driverless dump trucks, while the GPS is used to ascertain their position” [20].

Autonomous haul truck tests have been conducted by Komatsu at the Gaby open pit mine in Chile and the West Angelas mines in Western Australia [21]. Their system is heavily reliant on GPS to navigate haul trucks within the mine [22]. Caterpillar has taken similar steps by partnering with Carnegie Mellon University (CMU) to automate their haul truck fleet. CMU’s involvement in the DARPA (Defense Advanced Research Projects Agency) Urban Challenge, an autonomous vehicle competition, will fuel Caterpillar’s efforts to reach Komatsu’s level of automated implementations.
The most advanced systems in place (at the time of this report being written) use GPS, inertial measurement units (IMU) and wheel encoders to make an accurate estimate of the vehicle's location in order to maintain the vehicle on its path [23]. These haul trucks are only employed on closed circuit routes due to their inability to adequately assess their direct environment. This means that the vehicles are yet to be programmed on how to interact at traffic intersections, or to react to changes in topology such as berm sloughing and human operator interaction. In order to design fully-autonomous vehicles, each phase of the vehicle’s operation needs to be analyzed and modelled into the programmed behaviour (e.g., hauling, spotting, and queuing for haul trucks).

The major disadvantage of these systems is their reliance on High Precision GPS systems (HPGPS). GPS systems work consistently well in scenarios where the antennas have an unobstructed view of the sky to communicate with multiple satellites. Often, as mines increase in depth, GPS receivers are unable to communicate with multiple satellites, resulting in a reduction of accuracy or even complete loss of localization. Repeater stations (a.k.a. pseudolites) can be placed on upper benches to supplement GPS signals but don’t always improve performance. Poor GPS measurements can have a significant impact if a vehicle is to rely on this technology alone for automatic positioning and control of a robotic vehicle system. For this reason, the research presented in this report favours a GPS-less spotting system.

The candidate found little research pertaining to GPS-less autonomous systems for open pit mines. This is likely due to a variety of reasons; the advent of autonomous mining equipment being fairly recent, equipment suppliers are reluctant to disclose trade secrets, but most importantly, the reduction to relative-frame state estimation. Without GPS, it is difficult to determine a global position thus complicating multi-vehicle co-ordination. There are other ways
to obtain a global frame reference, such as using radio frequency stations to triangulate vehicle location, but these systems have similar shortcomings that GPS systems do. The research presented in this thesis focuses on using sensors that deduce relative-frame states.

As mentioned above, there is little research into the advantages and disadvantages of GPS-less equipment performing autonomous routines. For this reason, a look into commercial vehicle systems was undertaken.

2.4 Commercial Vehicle Automation

A haul truck spots to locations beside a shovel in almost the same way that a car backs into a parking spot. They pull up perpendicular to the location at which they want to park and slowly turn 90 degrees as they back into the spot. A haul truck does the same by pulling up perpendicular to the front of a shovel and slowly backing into the loading zone (depending on loading style as mentioned above). As there are commercially available automated parking systems, it seemed fit to take a look at their approaches to solving the autonomous parking problem. Several companies have commercially available systems; Toyota, Ford, BMW and Volkswagen are the most notable. Each company’s method works similarly, so a closer look into Lexus/Toyota’s Intelligent Parking Assist System (IPAS) is examined because they supply more information than their competitors [24].

Most of the systems work by initiating the parking assist feature briefly before pulling up to a parking spot. As the vehicle passes by the empty spot, ultrasonic sensors send out signals that sense points of importance; e.g., the corners of adjacent cars, the curb and any obstructions within the parking bay. An illustration of this process can be seen in Figure 9. “The sonar park sensors
include multiple sensors on the forward and rear bumpers which detect obstacles, allowing the vehicle to sound warnings and calculate optimum steering angles during regular parking” [25].

The driver then stops beside the vehicle in the adjacent spot and places the vehicle into reverse. At this point, the system assesses whether there is adequate space to park based on the location of the two vehicles and the curb. If there is an acceptable amount of space, the system will notify the driver so that they can initiate the parking process from the command console. If the user initiates the park, they will be instructed to remove their hands from the steering wheel and to keep their feet close to the brake during parking. The system will then assume control of the wheel articulation and throttle to control the vehicle into the parking bay. The system will notify the driver when the process is complete to place the vehicle into park. Details as to what control method is implemented are not provided. For the sake of testing this system, we will assume some form of path tracking system.

Figure 9: Top view of vehicle determining acceptable parking bay [26]
The IPAS is unique in that it allows the driver to adjust the location of the final parking spot via visual display on the vehicle’s dash as seen in Figure 10. Before the driver initiates the parking process, they can alter the parking location via on-screen controls to account for obstructions not identified by the scanning process. If a process similar to the visual assist parking could be implemented on a haul truck, a significant increase in spotting accuracy could result. A camera could be mounted on the haul truck or shovel to show the driver approximately where the vehicle will park if they initiate the parking sequence. These products suggest a potential framework for developing autonomous spotting systems, though alternative sensing options from the mining scenario need to be considered.

![Figure 10: IPAS Assisted Parking System HUD within a Lexus Vehicle [27]](image)

2.5 Sensor Options

Ultrasonic range-finding sensors have demonstrated suitability for automobile assisted park systems, though there are a variety of commercially available range-finding sensing technologies. A range-finding sensor works by sending out a pulse at a known rate, time of arrival after rebounding is recorded, and from this, distance can be estimated. The most common sensors are
LiDAR (Light Detection and Ranging), millimeter wave radar, and ultrasonic sensors. A comparative study of range-finding sensors could go into great length. To summarize some of the arguments:

- Photoelectric sensors use light pulses (e.g., lasers) to measure distances. They are highly accurate; most sensors can obtain sub millimeter accuracy. Photoelectrics struggle with translucence and high glare environments. They are also susceptible to degradation in dense aerosol environments [28]. Arguments can be made that, by varying beam width and applying computationally intensive filtering, obscurant penetrating solutions also exist [29].

- Ultrasonic sensors use pulses of ultrasonic sound to measure distances. Ultrasonics struggle with attenuation due to absorption. Reflectivity does not affect ultrasonic sensors. They are highly accurate at low ranges. They are less susceptible to obscurants than a photoelectric sensor. Radar system beams, including ultrasonic sensors, are confined to a narrow cone [30]. This means that the time-of-flight information determined by the sensor can be misconstrued, especially at great distances.

Assuming ideal conditions (i.e., low levels of obscurant, low lustre scanning surfaces) both categories of sensors would behave suitably. As environmental conditions become less ideal, each technology will react differently, suggesting a particular sensor should be selected on its qualities in the environment in which it will be deployed. A solution suitable for arid Nevada may not work in the humidity of the Dominican Republic, and vice versa. A LiDAR sensor was used for this research, specifically a SICK LMS111 [31]. SICK lasers are used widely in the research and industrial communities, and a variety of drivers and software tools for these devices have been developed to suit the needs of users.
3.1 Introduction

This chapter proposes a concept design for an auto-spotting system. Because there are numerous shovel loading configurations, the design proposed here focuses on single-sided loading of a shovel working on a frontal cut. A conventional “turn and back up” spotting procedure acts as the baseline action to model. A framework for determining a suitable loading location and how an autonomous navigation system could control a vehicle to that location is outlined.

3.1.1 Spotting Configurations

The configuration of a shovel’s cut greatly affects the path a haul truck driver must navigate in order to spot. A frontal cut, as seen in Figure 11, is an ideal digging configuration when a great deal of working area is available. It facilitates double-sided loading and reduces the average swing angle of the shovel to about 60° [12]. Most other digging configurations force the haul truck operator to perform a “turn and back up” spotting procedure.
The other important shovel configuration is a parallel cut. Bench development on upper levels is typically performed in this manner. A drive-by parallel cut is when a shovel traverses parallel to the digging face. It is very efficient (from a haul truck’s perspective) when bench access is available from both directions because the trucks are not required to back up when spotting to a shovel, though this is not usually possible. Typically, there is only access to the ramp from one side of the shovel. “Pit geometry is made up of a series of trade-offs. Steeper slopes result in a savings of stripping costs. In the other hand they can, by reducing operating space, produce an increase in operating costs” [12]. Often pit conditions will constrain the loading configuration. If the working bench width is too narrow, a shovel will only be able to have one truck in position for loading at a time.
When the bench width will allow double sided loading (Figure 12), the steps a haul truck driver takes to spot to its loading location are similar to the procedure for a frontal cut configuration. The haul truck turns and stops facing backwards to the back of the shovel, then spots to its loading location beside the shovel. For this reason, the auto-spotting system outlined in the text of this thesis will pertain to a frontal cut configuration. This is not to say that a design that utilizes double-sided loading could not be deployed. For example, the system could be mirrored by attaching another LiDAR to the other side of the shovel. The two systems could then use an identical framework for communicating between vehicles, though a model for determining to which side a haul truck should spot to would be required.
3.1.2 System Configuration

Now that a characteristic spotting configuration has been defined, it is necessary to outline how a spotting solution could be implemented (and tested). Traditionally, mobile robotic systems use onboard sensors to detect and evaluate environmental conditions [18]. This allows data capturing and processing to be performed quickly as all subsystems are connected locally. The downside to this method, especially in systems without absolute measurements, is determining relative position and orientation of a vehicle while it, and thus its sensors, are in motion. Another option is to have stationary sensors in the environment measuring the movement of the mobile vehicle, or some combination of both.

In the instance of auto-spotting, instead of installing LiDAR sensors on a haul truck and scanning ranges to a shovel, an alternative method would be to mount LiDAR sensors on the shovel and then scan for the haul truck. Some advantages and disadvantages to this design approach are outlined in Table 2.

Table 2: A comparison of shovel versus haul truck mounted LiDAR sensors

<table>
<thead>
<tr>
<th>Shovel-Mounted LiDAR Advantages</th>
<th>Shovel-Mounted LiDAR Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>• The LiDAR sensor is more stationary, therefore reduced noise introduced to the measurement.</td>
<td>• System complexity increases. Subsystems are not connected locally. Information shared between the shovel and truck will have to be sent over a wireless connection.</td>
</tr>
<tr>
<td>• Fewer LiDAR sensors are required. A couple of sensors on each shovel compared to at least one LiDAR</td>
<td>• System redundancy issues. One sensor on a shovel affects all haul trucks, whereas a faulty truck mounted sensor</td>
</tr>
</tbody>
</table>
This thesis suggests that a shovel-mounted scanning system would be better suited for an auto-spotting system. As mentioned in Table 2, a shovel-mounted sensor would require communication between the scanning subsystem on the shovel and the main routines, including estimation and control algorithms, running on the spotting haul truck. Wireless communication systems have been demonstrated in application numerous times [32] [33], therefore system design will not focus on wireless solutions. A standard high frequency radio signal communication system would be suitable to communicate sensor information at the desired system rate (10 Hz).

Another important design consideration is the limitation of haul truck location and orientation in relation to the shovel. There will be obvious limitations in how well an auto-spot system will be able to control a vehicle from an undesirable configuration into the optimal spotting location. For example, if the haul truck is initially too far or too close to the shovel, it will be impossible to spot to a suitable loading location. Ideally, a haul truck driver will have flexibility in the location at which he/she stops before commencing the spotting process. Based on observations made at Goldstrike Open Pit and the acquired data, an acceptable pre-spotting location zone was defined by the candidate. This zone can be seen in the schematic of Figure 13. The goal of the pre-spot zone is to define a region that when an auto-spotting system is initialized, the vehicle should be able to navigate to the desired loading location. The zone is limited in location and orientation
based on the turning radius of the RTV. The farther away the vehicle is from the loading location, a greater amount of lateral space is afforded to the spotting vehicle.

Figure 13: Schematic of the shovel-truck Pre-Spot Zone

The resulting zone is roughly the shape of a triangle; 2-3 haul truck lengths long and, at its base, 1-2 haul truck widths wide. Of course there has to be limitations with regards to the orientation of the haul truck. The centre axis of the haul truck can be no greater than 30 degrees (when acute) to the parking trajectory. When the centre of axis is obtuse to the parking vector, an interior angle of 10 degrees should not be exceeded; this is illustrated more clearly in Figure 14. This restriction is a result of the haul truck’s kinematics. The RTV has a large turning radius for reverse motion.
3.2 Auto-Spot Procedure

3.2.1 Auto-Spotting Operational Concept

This section outlines the framework for the auto-spotting procedure. The operational procedures listed below guided the design of the system described in this thesis (Figure 15).

1. Before spotting, the shovel operator designates a suitable loading location. The possible locations would be along a radius of 22 m (example swing radius) from the shovel’s centre (swivel) point. Allowing the shovel operator to set the loading location could mitigate problems involving non-ideal pit configurations.
2. When spotting is required, a haul truck operator turns the truck past the shovel, stopping in the pre-spot zone facing away from the shovel. During this time, a wireless communication link is established between the truck and shovel.

3. An approximate location of the shovel is determined from an initial LiDAR scan. A check is done to decide whether it falls into the acceptable pre-spot zone. If so, an indicator informs the haul truck and shovel operators that the truck is ready to spot. If not, the haul truck operator must realign the vehicle.

4. The haul truck operator puts the vehicle into reverse and initiates the auto-spotting process. An indicator now shows that the system is in auto-spotting mode. At this point, the estimator has been running for several hundred cycles and has a ‘lock’ on the vehicle.

5. The automatic vehicle controller drives the truck to the designated loading position and orientation. In this style of control, an indicator could inform the driver when he has reached the designated location so they can disengage the throttle and apply the brake.

6. At this point, if successful, the haul truck has spotted to the suitable loading location. The system applies the brake and prompts the driver to re-accept control of the truck from the auto-spotting system. This process may vary depending on the style of haul truck. If unsuccessful, the operator may have engaged an emergency stop (e-stop) switch or taken over manually for some other reason. Because this process is performed at low speeds, the user should have ample time to assess dangerous actions and if necessary, engage safety measures. A warning system should be implemented to identify proximity threats.
Figure 15: Flowchart of operational procedures for the auto-spot system
3.2.2 RTV Spotting Experiments

An experimental setup was designed to test the proposed algorithms while simulating realistic conditions. This section outlines the experimental setup and the materials used for an auto-spotting experiment carried out using a robotic Kubota RTV.

The Caterpillar 797 and the Komatsu 930 are two popular models of haul truck. Both manufacturers have models of these vehicles that are automation-ready [20] [34]. A fleet of sensors and controllers are embedded into these vehicles so that autonomous routines can be performed. For an auto-spot system, or any routine that requires vehicle navigation, several variables need to be measured; wheel speed, steering angle, throttle and brake position, gearing, etc. Our robotized Kubota RTV serves to emulate these haul truck features. The RTV has dual wheel encoders on the front tires to measure vehicle velocity, linear potentiometers on throttle and brake levers and a contactless absolute encoder mounted on the steering linkage. The RTV’s GPS system also features an embedded gyro to measure vehicle rotation rate. These sensors, with accompanying servo controlled throttle, brake and steering, allow the RTV to behave similarly to an automation-ready haul truck. Unfortunately, the gear selector on the RTV is manually controlled by a lever. This poses a limit on the testing procedure described in this thesis.
The other major element of the system is the shovel subsystem. This was simulated by using a cart-mounted LiDAR scanner and wireless transmitter for communicating with the main system on the RTV. The communication system is illustrated in Figure 16. It is proposed that an auto-spot design that accommodates double-sided loading would consist of two LiDAR sensors mounted on the back corners of a large electric cable shovel; i.e., a P&H 4100C or CAT 7495. These styles of shovels have a large back frame, so there is flexibility in the mounting locations. As the system would act symmetrically on each side, only a single-sided system is modelled in this thesis.
In our experiments, a LiDAR sensor was mounted at a fixed height to scan a plane that intersects the side profile of the RTV. The experimental setup, viewed from above, is shown in Figure 17. The effect of the scanning height and the profile used for scan matching can be found in Section 6.2.3. A SICK LMS 111 LiDAR sensor operating at a frequency of 25 Hz and at resolutions of 1.0 and 0.5 degrees was used. A standard off the shelf router (Linksys WRT54G) was used to communicate with the main system on the RTV. Communication between sensors and subsystems was done over Ethernet via TCP/IP protocols.

Figure 17: Overhead view of the experimental setup for the auto-spot system

This experimental setup utilized the Robot Operating System (ROS) environment on the Ubuntu Linux platform as the software backbone for all computing infrastructure. As mentioned in the introduction, the Kubota RTV was developed to use ROS for all sensor data logging, command I/O and safety systems. ROS is a software framework that can ‘wrap’ user generated C++ and Python computer code. It provides standard services such as device control, message-passing between processes, and node management. This means that several processes can be running
simultaneously that receive and send sensor, control, and state estimation data. The process design within the ROS infrastructure is outlined in greater detail in Section 5.2.

The development of the simulation environment was done MATLAB® (a numerical computation and programming software package). MATLAB® has similar functionality to ROS in that it processes user generated code between multiple subsystems. Instead of a functioning RTV, the simulation environment used was a kinematic model of the RTV to simulate vehicle behaviour. Similarly, vehicle sensors were modeled and simulated based on vehicle kinematic model outputs; i.e. velocity, turning rate, etc. Simulation design is discussed more thoroughly in Chapter 4.

3.2.3 Optimal Loading Location

Section 3.1.4 outlined the results of a field trip to Nevada to collect GPS trace data from haul trucks and shovels at the Goldstrike operation. As expected, the average distance from the shovel centre to the haul truck bed centre was approximately equal to the shovel swing radius (22 m). Large variability was observed in the average distance to working face. This suggests that a suitable loading location would be along a radius of 22 m from the shovel’s centre of mass but an appropriate orientation was poorly defined by the data. Exactly where along that radius will be a function of several factors, such as, the location of the working face. Ideally, this location could be set by the shovel operator as the optimal loading location varies as the face advances. In practice, this would allow the more experienced operator, with a better view of haul truck movement, to account for pit conditions and the orientation of the working face. Though, this will add additional tasks for the operator.

As the loading location has to be along the bottom half of the loading zone seen in Figure 18, the haul truck will be within scanning range of the LiDAR. Therefore, the loading location along the
shovel swing radius does not greatly affect system functionality. The haul truck orientation should not exceed a certain angle from the desired path to ensure the haul truck bed is aligned with the shovel dipper to minimize contact occurrences. This angle will differ depending on truck bed and shovel dipper size. For the design within this report, an angle less than ±10° is desired.

The parking angle, $\theta_p$, was set to 90° from the shovel digging vector, which should, in most cases, be approximately parallel to the working face. This can be seen in Figure 18, but could be a parameter of the system. This selected orientation is consistent with the collected data. Typically, a shovel operator will orientate the shovel tracks to face the advance and thus stabilize the shovel footing during excavation. This location minimizes the swinging angle of the shovel while keeping a safe distance from the face.

The path of the RTV, or an autonomous haul truck, is controlled by an onboard control system. The experiments outlined within this text utilized a path tracking controller to determine vehicle inputs, this is outlined further in Section 4.2.3. In an attempt maintain simplicity of the experiments, a line perpendicular to the working face was used as the default spotting path. Section 6.2.2 discusses the effect of changing the angle of this vector.
3.3 Kinematic Vehicle Model

The first step to modelling the RTV for pose estimation is to define the kinematic equations that govern the movement of the vehicle. Figure 19 illustrates the RTV system variables; the system is based on a backwards moving vehicle to more accurately depict vehicle movement. Let $q = (x, y, \theta)$ be the pose (position and orientation) of the centre of the RTV’s rear axle and the steering angle be denoted as $\phi \in \left(-\frac{\pi}{6}, \frac{\pi}{6}\right)$ all at times $t$. 

Figure 18: Loading configuration of shovel (grey) and truck (green) around shovel swing radius (red)
Figure 19: Kinematic model of Kubota RTV with positive reverse motion

The nonlinear discrete-time kinematic model used to define vehicle motion is defined as

\[
\begin{bmatrix}
\dot{x} \\
\dot{y} \\
\dot{\theta} \\
\dot{\phi}
\end{bmatrix} =
\begin{bmatrix}
0 \\
0 \\
0 \\
1
\end{bmatrix}
\begin{bmatrix}
v_1
\end{bmatrix}
+ \begin{bmatrix}
\cos(\theta) \\
\sin(\theta) \\
-\tan(\phi) \\
a \\
0
\end{bmatrix}
\begin{bmatrix}
v_2
\end{bmatrix}
\]

\[
v_1 = \dot{\Phi} = \omega \\
v_2 = \sqrt{\dot{x}^2 + \dot{y}^2} = V \\
\]

\[a = 1.985 \text{ m} \quad (1)\]

The linear speed and steering rate inputs are \( V \) and \( \omega \), respectively. The distance between axles is denoted as \( a \). This system utilizes several sensors that have to be defined:

- GPS;
- a gyro;
- a laser scanner;
- wheel and steering encoders.

These sensors are simulated by building a mathematical model for each one that also attempts to model the measurement noise as Gaussian white noise.
The steering angle is measured by a contactless absolute encoder mounted on part of the steering linkage. Let it be designated by

\[ \Phi + n_\Phi = \omega_{\text{steer}} n_\Phi \sim \mathcal{N}(\sigma^2_{\text{steer}}) \] (2)

Where \( n \) represents a Gaussian random variable with zero mean and a standard deviation, \( \sigma \). Sigma values pertaining to each measurement can be found in the Nomenclature section. The gyroscope built into the Trimble GPS Solution measures rotation rate

\[ \dot{\theta} + n_\theta = \omega_{\text{RTV}} n_\theta \sim \mathcal{N}(\sigma^2_{\text{RTV}}) \] (3)

Let the Hall effect sensors mounted on the front wheels measure ticks on the 40 tooth gear mounted to the wheel hub. The wheel circumference was calculated to be 1.88 metres. As two ticks are registered for each gear, the effective encoder scale is 0.0235 m/tick. Wheel velocity can thus be determined by

\[ \Delta \text{ticks} \times 0.0235 = \Delta \text{distance} \]

\[ \Delta \text{distance} / \text{time} = dV \]

\[ dV + n_v = dV_{\text{encoder}} n_v \sim \mathcal{N}(\sigma^2_{\text{encoder}}) \] (4)

Let the laser scanner measure ranges

\[
\begin{bmatrix}
  r_1 + n_1 \\
  r_2 + n_2 \\
  r_k + n_k
\end{bmatrix}
= z_k = h(q_k) n_k \sim \mathcal{N}(\sigma^2_z) \] (5)

Note that \( z_k \) is a column of height \( k \), where \( k \) is the number of scans; a function of LiDAR resolution. A resolution of 0.5 and 1 degree (resulting in 361 and 181 scans, respectively) were used for the experiments described in this thesis.
3.4 Control Algorithms

Chapter 1 outlined the difficulties in defining an optimal loading location. Assuming that we have a desired loading location; this section outlines the algorithms used to calculate the control outputs to navigate the RTV to the desired loading location. First the error model is defined. It is illustrated in Figure 20.

\[ \Theta = e_H \]

\[ e_L = y \]

**Figure 20:** Error states of Kubota RTV from desired spotting path

Then two error equations are defined to control the system back to ‘zero’, \( e_H \) and \( e_L \), as seen in Figure 20. The vehicle orientation error, \( e_H \), is equal to the vehicle orientation, \( \theta \), minus the desired path orientation, \( \theta_{path} \).

\[ e_H = \theta - \theta_{path} \quad (6) \]

This error changes over time, represented by \( \dot{e}_H \), which is equal to the change in motion for the vehicle orientation, \( \dot{\theta} \). From Equation (1) we get

\[ \dot{e}_H = \dot{\theta} = \frac{-V\tan(\phi)}{a} \quad (7) \]

The path error, \( e_L \), is equal to the distance between the desired path and the vehicles location perpendicular to the desired path. Over time, this error will change and thus be calculated from the vehicle orientation error as

\[ \dot{e}_L = V \sin(e_H) \quad (8) \]
These equations are then simplified to

\[
\begin{bmatrix}
\dot{e}_L \\
\dot{e}_H
\end{bmatrix} = \begin{bmatrix}
0 & \sin(e_{H,k-1}) \\
1 & 0
\end{bmatrix} \begin{bmatrix}
v_1 \\
v_2
\end{bmatrix}
\]  \hspace{1cm} (9)

Next, a control input, \(u\), is determined through a process called feedback linearization [35]. Transformations are made to Equation (9) so that a non-linear system can be controlled as it is easier to work in a different set of coordinates.

\[
c_1 = e_L \quad \dot{c}_1 = V \sin(e_H) = c_2
\]

\[
c_2 = V \sin(e_H) \quad \dot{c}_2 = V e_H \cos(e_H) = -\frac{v^2}{a} \tan(\phi) \cos(e_H)
\]  \hspace{1cm} (10)

Therefore input, \(u\), is equal to

\[
u = -\frac{v^2}{a} \tan(\phi) \cos(e_H)
\]  \hspace{1cm} (11)

Equation (11) then defines the controller

\[
\dot{c} = A \dot{c} + B \ddot{u}
\]  \hspace{1cm} (12)

The poles of the control system are the eigenvalues of \(A\). Using the state feedback control law [36]

\[
\ddot{u} = -K \dot{c}
\]  \hspace{1cm} (13)

This gives

\[
\dot{c} = A \dot{c} - BK \ddot{c}
\]

\[
\dot{c} = (A - BK) \dot{c}
\]  \hspace{1cm} (14)

Where \((A - BK)\) is the closed loop equation of the system. This demonstrates that state feedback changes the pole locations (which is expected of feedback). The closed-loop poles are determined by the eigenvalues of \((A - BK)\). We can simplify Equation (10) using Equations (12) into

\[
\dot{c} = \begin{bmatrix}
0 & 1 \\
0 & 0
\end{bmatrix} c + \begin{bmatrix}
0 \\
1
\end{bmatrix} u
\]  \hspace{1cm} (15)
3.5 Localization

Localization of the RTV requires the estimation of the vehicle’s pose as it spots beside a shovel in an unknown environment. Numerous techniques have been developed to solve vehicle pose estimation. One of the most common techniques is to employ a Kalman filter. The Kalman filter is an algorithm that fuses observed measurements over time to produce estimates that are typically more accurate than then any single measurement [37]. It operates by propagating the mean and covariance of the estimate through time. The standard Kalman filter is limited to linear systems; often more complex systems (such as the RTV) are nonlinear. The extended Kalman filter (EKF) can be used when a non-linear system can be linearized; that is, a matrix of partial derivatives (a Jacobian) is calculated [38]. Another technique for handling nonlinearities is the unscented Kalman filter (UKF). The UKF does not linearize the system models, but rather utilizes an unscented transform to determine a minimal set of sigma (sample) points (based on the number of modelled vehicle states) that can be propagated through the non-linear system equations and then recaptured [37]. This technique is preferable to the extended Kalman filter, when possible, as Jacobians are not required to be calculated and it is a more accurate representation of the nonlinear system.

The final experimental design outlined in this report utilized an unscented Kalman filter (UKF). This technique has been used in other automated mining equipment systems when the vehicle is operating in an unknown environment. Marshall, Barfoot and Larsson suggest this method because “the task at hand does not require a solution to the global localization problem; we need only track the vehicle’s motion relative to the profiled path” [39]. The profiled path for the case of the auto-spotting system would be the desired path denoted in Figure 17. The UKF fuses an initial vehicle pose estimate (prediction), based on odometry (measurements on board a vehicle; wheel and steering encoders) data, with a secondary pose estimate (correction) to produce a more
accurate state estimation. Multiple estimation techniques were used in the experiments outlined in this report; the variations that led to the final design are outlined within this section.

The techniques used herein assume that the vehicle has adequate footing and an unobstructed path to the loading location. In analog environments, these conditions may not always be true. Vehicle operations in these adverse conditions lie outside of the scope of this research. Also, a comprehensive safety system would need to be implemented in order to ensure the safe operation of driverless vehicles in the mine.

3.5.1 Vehicle Pose Initialization

One problem with state estimation solutions that utilize a Kalman filter is the uncertainty of the initial pose. If the initial pose of the vehicle is unknown at the start of a sequence, a best-guess has to be defined in order to establish a baseline for vehicle motion propagation. In the case of the auto-spotting problem, the first rendition of the experimental setup fixed the initial guess to the centre of the pre-spot zone (Figure 13). This was found to be suitable for experiments with small perturbations in initial error but thus limited the acceptable pre-spot zone. To circumvent this issue, a pre-routine LiDAR scan was measured to estimate the vehicle’s initial pose. Essentially, visible\(^1\) ranges were averaged with a pre-set orientation to give a more accurate initial estimate.

3.5.2 Extended Kalman Filter (EKF)

As mentioned previously, the final system design presented in this thesis utilizes an unscented Kalman filter to fuse estimation algorithms. Alternative solutions were tested to act as a baseline for comparative measurements and as a development stage. One of those techniques utilized an unscented Kalman filter to fuse estimation algorithms. Alternative solutions were tested to act as a baseline for comparative measurements and as a development stage.

\(^1\) Depending on the model, a LiDAR will output a null measurement as either full or zero range. An visible range is defined as a non-zero measurement with a range output less than the LiDAR’s max range i.e. \(0 < \text{observable} < \text{range}_{\text{max}}\).
extended Kalman filter (EKF) [37]; this begins with our discrete-time model from Equations (7) and (8)

\[ e_k \approx e_{k-1} + TG(e_{k-1})(U_k + W_k) \quad (16) \]

We then add process noise

\[ Q = \begin{bmatrix} \sigma_{en}^2 & 0 \\ 0 & \sigma_{gyro}^2 \end{bmatrix} V_k - N(O, R) W_k - N(O, Q) \quad (17) \]

This results in the model

\[ \begin{bmatrix} \dot{e}_L \\ \dot{e}_H \end{bmatrix} = \begin{bmatrix} 0 & \sin(e_{H,k-1}) \\ 1 & 0 \end{bmatrix} \begin{bmatrix} v_{1,k} \\ v_{2,k} \end{bmatrix} + W_k \quad (18) \]

The measurement model samples \( \phi \) and \( V \), and is thus defined as

\[ Z_k = \begin{bmatrix} \phi_k \\ V_k \end{bmatrix} = Cq_u + V_k \quad (19) \]

Computing the Jacobians

\[ F_k = \frac{\partial f}{\partial \dot{q}_k} = I_2 + \begin{bmatrix} 0 & \cos(e_H) \\ 0 & 0 \end{bmatrix} \quad (20) \]

\[ L_k = \frac{\partial f}{\partial w_k} = TG(\dot{q}_k^+) \quad (21) \]

The positive and negative superscript symbols represent the variables the correction and prediction step, respectively. A prediction estimate is then

\[ P_{k+1}^- = F_k P_k^+ F_k^T + L_k Q L_k^T \quad (22) \]

\[ \dot{q}_k^- = f(\dot{q}_k^+, u_k, w_k) \quad (23) \]

Our initial objective was to compare estimators that use GPS to methods that do not use absolute measurements. For this reason, this EKF model uses a GPS signal as its corrective measurement. Let the GPS measurement

\[ \begin{bmatrix} x + n_{GPS} \\ y + n_{GPS} \end{bmatrix} = h \quad n_{GPS} \sim N(0, \sigma_{GPS}^2) \quad (24) \]
The Jacobians for the observation model are thus defined as

\[ H_k = \frac{\partial h}{\partial q_k(q_k)} = [1 \ 0] \]  \hspace{1cm} (25)

\[ M_k = \frac{\partial h}{\partial u_k(q_k)} = 1 \]  \hspace{1cm} (26)

A corrective estimate is then processed from the predictive estimate. From Equation (22)

\[ K_{k+1} = P_{k+1}^- C^T (C P_{k+1}^- C^T + R)^{-1} \]  \hspace{1cm} (27)

\[ \hat{q}_{k+1}^+ = \hat{q}_{k+1}^- + K_{k+1} (z_{k+1} - C \hat{q}_{k+1}^-) \]  \hspace{1cm} (28)

\[ P_{k+1}^+ = (I_2 - K_{k+1} C) P_{k+1}^- \]  \hspace{1cm} (29)

### 3.5.3 Unscented Kalman Filter (UKF)

The final system design utilized a UKF [37]. As mentioned previously, this method is beneficial as it does not have to calculate the Jacobians of the non-linear system. The algorithm begins with our discrete-time model given by Equation (1)

\[
\begin{bmatrix}
\dot{x} \\
\dot{y} \\
\dot{\theta} \\
\dot{\phi}
\end{bmatrix} =
\begin{bmatrix}
0 \\
0 \\
\cos(\theta) \\
-\tan(\phi)/a
\end{bmatrix} v_1 +
\begin{bmatrix}
\cos(\theta) \\
\sin(\theta) \\
0 \\
0
\end{bmatrix} v_2
\]

\[ v_1 = \dot{\phi} = \omega \]

\[ v_2 = \sqrt{\dot{x}^2 + \dot{y}^2} = V \]

\[ a = 1.985 \text{ m} \]

With process noise

\[ Q = \begin{bmatrix}
\sigma_{en}^2 & 0 \\
0 & \sigma_{steer}^2
\end{bmatrix} W_k N(Q_{en}, Q_{steer}) \]  \hspace{1cm} (30)

Where \( Q_{en} \) and \( Q_{steer} \) were 0.01 (m) and 0.01 (rad), respectively. The simplified system model is thus

\[
\begin{bmatrix}
\dot{x} \\
\dot{y} \\
\dot{\theta} \\
\dot{\phi}
\end{bmatrix} =
\begin{bmatrix}
0 \\
0 \\
\cos(\theta) \\
-\tan(\phi)/a
\end{bmatrix} v_1 +
\begin{bmatrix}
\cos(\theta) \\
\sin(\theta) \\
0 \\
0
\end{bmatrix} v_2
\]

\[ v_1 = \dot{\phi} = \omega \]

\[ v_2 = \sqrt{\dot{x}^2 + \dot{y}^2} = V \]

\[ a = 1.985 \text{ m} \]  \hspace{1cm} (31)
The observation model of the LiDAR is defined by

\[
\mathbf{z}_K = \begin{bmatrix}
    r_{1,K} + n_1 \\
    r_{2,K} + n_2 \\
    \vdots \\
    r_{n,K} + n_n
\end{bmatrix} = \begin{bmatrix}
    r_{1,laser} \\
    r_{2,laser} \\
    \vdots \\
    r_{n,laser}
\end{bmatrix} = h(q_k) \quad V_K \sim N(R) \tag{32}
\]

A multiplier \( R_{mutt} \) (ranging in value from 1000 to 2500) was applied to the observation error \( R \) (0.1) in order to balance the covariance models. This is due in part to the array of ranges measured in the correction step. If the multiplier \( R_{mutt} \) was not applied to the observation error \( R \), then the correction estimate would weigh the prediction and correction measurements equally.

In this design, it is more suited to consider the array of correction measurements as one single measurement. The value of \( R_{mutt} \) will fluctuate depending on the number of system measurements and their relative error.

The UKF is initiated by computing the expected state using

\[
\hat{x}_0^{+} = x_0 \tag{33}
\]

Sigma points are generated based on

\[
\hat{x}_k^{(i)} = \hat{x}_k^{+} + \tilde{x}^{(i)} \quad i = 1, 2, \ldots, 2n
\]

\[
\tilde{x}^{(i)} = \left( \sqrt{nP_{k-1}} \right)_i \quad i = 1, 2, \ldots, n \tag{34}
\]

\[
\tilde{x}^{(n+i)} = -\left( \sqrt{nP_{k-1}} \right)_i \quad i = 1, 2, \ldots, n
\]

Where \( \sqrt{nP} \) is the matrix square root of \( nP \), such that \( \left( \sqrt{nP} \right)^T \left( \sqrt{nP} \right) = nP \) and \( \left( \sqrt{nP} \right)_i \) is the \( i-th \) column of \( \sqrt{nP} \). The prediction step is initiated by propagating the sigma points through the system model by

\[
\hat{q}_k^{(i)} = f \left( \hat{x}_k^{(i)} \right), i = 1, 2, \ldots, 2n \tag{35}
\]

The resultant mean and covariance are then averaged based on
Now we update the estimate by computing the sigma points based on the new mean and covariance

\[
\hat{x}_k^- = \frac{1}{2n} \sum_{i=1}^{2n} \hat{x}_k^{(i)} 
\]

\[
P_k^- = \frac{1}{2n} \sum_{i=1}^{2n} (\hat{x}_k^{(i)} - \hat{x}_k^-) (\hat{x}_k^{(i)} - \hat{x}_k^-)^T + Q
\]  (36)

\[
P_y = \frac{1}{2n} \sum_{i=1}^{2n} (\hat{y}_k^{(i)} - \hat{y}_k^-) (\hat{y}_k^{(i)} - \hat{y}_k^-)^T + R
\]  (37)

The sigma points are then propagated through observation model

\[
\hat{z}_k^{(i)} = h(\hat{x}_k^{(i)})
\]  (38)

And recombined based on

\[
\hat{z}_k = \frac{1}{2n} \sum_{i=1}^{2n} \hat{z}_k^{(i)}
\]  (39)

The Kalman filter equations are then applied

\[
P_y = \frac{1}{2n} \sum_{i=1}^{2n} (\hat{y}_k^{(i)} - \hat{y}_k^-) (\hat{y}_k^{(i)} - \hat{y}_k^-)^T + R
\]  (40)

\[
P_{xy} = \frac{1}{2n} \sum_{i=1}^{2n} (\hat{x}_k^{(i)} - \hat{x}_k^-) (\hat{y}_k^{(i)} - \hat{y}_k^-)^T
\]  (41)

\[
P_k^+ = P_k^- - K_t P_y K_t^T
\]  (42)

The corrective estimate is then updated based on

\[
K_k = P_{xy} P_y^{-1}
\]  (43)

\[
\hat{x}_k^+ = \hat{x}_k^- + K_k (z_k - \hat{y}_k^-)
\]  (44)

\[
P_k^+ = P_k^- - K_t P_y K_t^T
\]  (45)

Where \( \hat{x}_k^+ \) is the updated state estimate and \( P_k^+ \) its associated uncertainty covariance.
Chapter 4 Simulation

4.1 Introduction

This chapter describes how a model of the system in a computer simulation environment was built to study and debug the algorithms generated in Chapter 3, prior to implementation in hardware. The first phase was to conceptualize the overall system design. Figure 21 illustrates the initial block model. The four main sections of the system are: the vehicle kinematics, the sensors, the estimator, and the controller.

The vehicle block contains the kinematic equations that govern the movement of the RTV. The vehicle inputs; velocity $V$ and steering angle $\phi$, are inputs to the kinematic equations of motion. The integrated state variables from the vehicle block are then sent to the simulated sensors. The calculated sensor states are then relayed to the estimator. Once the estimator runs its routines, the estimated error states are sent to the control block. The control block determines the appropriate steering angle (based on a set speed) and outputs this value to the kinematic model thus closing the control loop.

The system model uses a constant velocity input. This was assumed acceptable for a low speeds (0.4 m/s). Future versions will need a throttle controller to account for environmental disturbances, such as uneven footing.

The entire system was designed to operate at 10 Hz; this was considered as the minimal rate that would facilitate estimator operation as the ROS vehicle input required a steady signal rate of at least 10 Hz; otherwise the low-level ROS controller would modulate the throttle at the lower prescribed frequency.
4.2 Simulator Development Process

One of the most important lessons learned from this experience was that it is important to check that each module of the system works independently before integrating it into the system. It is also crucial to ensure that any change made to one model does not cripple the functionality of another. The development phases for the simulator are outlined next and are depicted in Figure 22. The final system design as built in MATLAB’s SIMULINK® is illustrated in Figure 23 and described next.

- **Kinematic Model:** The first block of the system model constructed contained the vehicle kinematics. This block accepts keyboard inputs for vehicle velocity \( V \), and steering angle \( \phi \) to drive the virtual vehicle kinematics in the 2-D environment.

- **Sensor Models:** Once the kinematic model was operational, the simulated sensors were implemented. This block accepts the RTV state variables, computes what the sensors would measure (Equations 2-5), and adds representative noise for output.
• Estimator: In this block, the sensor outputs (Equations 2-5) are read in and an estimate of the vehicle’s pose is calculated. The predictive estimate is based on speed and angular rate inputs. Once the predictive estimate was operating properly, a corrective estimator step was applied to the estimated pose. The first correction algorithm implemented was an EKF based on simulated GPS reading. Further development updated this process to a UKF that utilized the shovel-based laser scan.

• Controller: This module accepts the pose estimate from the estimator and calculates the desired steering angle based on a fixed speed (0.4 m/s). The steering angle is then passed to the vehicle model. The keyboard input module developed in Phase 1 was modified to allow switching between manual and control algorithm inputs.
Figure 22: Auto-Spot block model phase development
4.3 Results

In order to test the effectiveness of the development algorithms, the estimated vehicle pose error was calculated at each time step. In the subsequent plots, you will see that each state error is bounded by \( \pm 3\sigma \), i.e. plus and minus three sigma of the state’s variance. The variance represents with what level of confidence we assign the estimate. If the error is within \( \pm 3\sigma \) then, assuming that the Gaussian assumption holds, we are 99.7% sure that the estimate falls within that range.

4.3.1 Extended Kalman Filter

Once the prediction step of the estimator was developed, the estimator was tested to ensure the sensor models were producing accurate measurement errors. This means that the estimator would accept sensor data and predict the pose of the vehicle based solely on the RTV’s kinematic equations. Since there is no corrective step in this estimator, the covariance will increase with time without bounds due to the integration of sensor and process noise.

The corrective estimator step was then applied to the estimator using a GPS signal as the corrective measurement (Figure 25). This was designed to be a stepping stone in the process of
creating a suitable estimator for the auto-spotting application. It also serves as a comparative model for a LiDAR based estimator. The absolute measurement of the GPS system is an obvious sensor choice when a sufficient number of satellites are continuously available.

Figure 24: RTV simulating dead reckoning of state error

Figure 26 shows the estimated errors after applying a GPS-based corrective step to the estimator. One can see that the estimate does not accurately assess the GPS error. This is due to the estimator underestimating the measurement error which leads to the vehicle position measurement ‘floating’ away from the actual location. This case was seen in the GPS traces recorded at the Goldstrike Open pit. Looking back to Figure 24, it can be interpreted that the estimator could be better off dead reckoning during poor GPS signal. While this isn’t a practical approach to vehicle automation, it demonstrates the requirement for reliable sensing systems.
Figure 25: Error analysis of EKF estimator using GPS

Figure 26: Effect of incorrect GPS signal to EKF estimator
4.3.2 Unscented Kalman Filter

Once the GPS-based EKF estimator was operating efficiently, a UKF utilizing a simulated LiDAR scanner was implemented. The same predictive step was applied; both models used the RTV kinematic equations to predict vehicle pose updates. Figure 27 shows the estimator error of the vehicle while being driven manually. The Figure also includes a subplot containing the number of visible LiDAR points per time step. This value is an important measure of the corrective process within the estimator; the number of LiDAR points corresponds to the number of data points used in the corrective estimator step. Once the estimator was functioning properly, the control algorithm was implemented. Figure 28 illustrates a ‘best case’ scenario spotting routine; initial state and controllable error is relatively zero so serves as a baseline for a successful UKF spotting procedure.

![Vehicle Pose Error of UKF](image)

**Figure 27:** State estimation error during manual operation
Figure 28: State estimation error during optimal spot routine

Figure 29 illustrates a spotting routine with a representative amount of error; i.e., the initial location is within the pre-spot zone (Figure 13). As one can see, the results are nearly indistinguishable to the plots seen in Figure 28. It appears the estimator took longer to converge on the vehicle location, as represented by the slower decrease in the \( \pm 3\sigma_s \) calculation. This result is expected because the fewer visible LiDAR points available, the less confident the estimator will be in its estimate. Next, a series of experiments were performed to determine the limitations of the pre-spot vehicle pose.
In order to determine suitable operating bounds, a schematic of varying starting locations and orientations was defined (Figure 30). The test locations were determined by scaling down the region in which a shovel stops before spotting. Location two is an ideal starting location, but other positions were defined in order to facilitate non-ideal conditions. Adding pre-spot locations to either side of the desired path, with varying orientations, simulated reasonable haul truck spotting conditions.

The RTV was placed in these locations with an angle of orientation +/- 30° to the parking vector to determine whether the system could be controlled to the desired loading location. With expected noise on each sensor, the simulated RTV was able to spot within a radius of 1 m of the loading location in 100% of the conducted experiments. It is important to note that while the simulation results were very successful, they do not accurately represent the reliability of an
implemented solution of the design. The simulator’s function was to test whether the design and algorithms were ready for field testing. It was also a useful tool for gauging the tunable variables, such as the controller gains.

![Figure 30: Pre-Spot test locations schematic](image)

When the desired operational bounds (+/- 2 m from the desired path) of the pre spot zone were broken, mixed results were observed. The position of the RTV had lesser effect on whether the estimator was able to converge on its location than that of the orientation. It was clear that as long as the vehicle was fully within scanning range, vehicle position localization was possible. The limiting factor in this case was the number of visible LiDAR ranges.
The most influential factor in successful localization was vehicle orientation. If the starting orientation of the vehicle was greater than +/- 30° from the initial guess (tangent to the parking vector) then the chance of successful localization varied dramatically. This is expected from a UKF estimator. One of its main flaws is the requirement for an accurate initial estimate. In the event that the initial estimate of the orientation of the vehicle was incorrect, a dramatic effect on the effectiveness of the predictive estimate was observed. Recall, from the vehicle kinematic equations (Equation 1), each of the state estimates is directly affected by vehicle orientation. To this end, many tests were conducted to determine the effect of noise on the steering encoder sensor. If significant amounts of error, representative of a low-end sensor (+/- 30% of the measurement), were added to the steering measurement then the vehicle pose estimate was corrupted (Figure 31). The update from an absolute measurement, such as a GPS reading, for example, would help to correct the location error from the orientation estimation failure.

Figure 31: State estimation error with $\Theta$ initially greater than 30° from the desired path
4.4 Summary Discussion

It was demonstrated that the simulated RTV is capable of spotting to the desired loading location when initiated within the acceptable pre-spot zone. When given error representative of analog conditions, the LiDAR-based UKF estimator is able to localize the vehicle to a high enough degree to facilitate a successful operation of the control algorithm. When the simulator was initiated with significant error (greater than two metres from the pre-spot locations or an orientation greater than 30° from the desired path), the system was less successful in spotting the RTV. The simulator was built as a tool to assist the system’s design and validate the generated algorithms before testing them on a real vehicle. The models used are typically detailed enough to represent analog conditions, but obviously do not incorporate all aspects of the actual system. The results of this application and testing are discussed in Chapter 5.

One of the main concerns identified within the simulated results was the effect of the initial vehicle orientation error. If the initial orientation was greater than +/- 30° to the parking vector then the estimator was unable to localize on the simulated RTV. Failure was also apparent when considerable noise was introduced to the steering measurement. This was identified as a concern within simulation but rectified by increasing the significance of the corrective estimate. Whether this is possible in application will reflect the effectiveness of a LiDAR based UKF estimator. The application of the above developments on a real vehicle is described next, in Chapter 5.
Chapter 5 Kubota RTV Testing

5.1 Introduction

This section details the development of the auto-spotting system on the autonomous RTV and presents the results collected from the field tests at Queen’s University. The automation-ready RTV was designed to act as a test bed for prototyping in that it possesses many of the same physical characteristics of a similar mining scenario. Many factors that reproduce approximately realistic conditions were used, such as the diesel-powered Kubota RTV, commercial grade LiDAR, and outdoor conditions. Testing mining equipment in representative conditions is difficult and costly as it is not usually possible to disrupt mine operations for prototype testing purposes. The RTV is a valued substitute as it possesses many of the same functional elements to a mining truck, at least more so than a servo controlled lab robot. Moreover, the vehicle is relatively simple to transport to mining operations and is certified to be used in open pit and underground mines. The RTV also has similar technical challenges, such as steering, throttle, and brake dynamics, similar to what a conventional haul truck would exhibit.

The RTV was stored and operated at Queen’s Innovation Park, which is an industrial facility near the Queen’s main campus in Kingston, ON. The site featured a large warehouse for indoor storage for the vehicle as well as a large outdoor paved pad for vehicle testing. This is where auto-spotting tests were conducted (see Figure 32). There was enough space to carry out a scaled version of the experimental setup illustrated in Figure 17.

The apparatus used for this testing included:

- Automation ready Kubota RTV with on-board odometry sensors:
- Contactless absolute encoder mounted on steering linkage
- Off the shelf Hall effect sensors on both front wheels
- Gyroscope built into Applanix IMU

- Applanix IMU+GNSS GPS system
- DGPS base Station with NovAtel GNSS receiver and Microhard wireless radio
- SICK LMS 111 LiDAR mounted to portable work station
- Linksys WRT54G Wireless router for RTV/LiDAR/computer communication and peripheral ethernet wires
- Motomaster Eliminator power pack to power LiDAR and miscellaneous electronics
- RTV Operator to monitor safety system on RTV

Figure 32: Kubota RTV with spotting hardware at Innovation Park testing facility

The RTV was placed in the pre-spot locations (see Figure 30), the spotting routine was initialized and the RTV was automatically driven to the loading location. In order to simulate a mining
environment as closely as possible, the pre-spotting locations of the RTV were scaled based on haul truck size. The pre-spotting locations and orientations are outlined in Figure 13.

Table 3: Pre-Spotting test locations

<table>
<thead>
<tr>
<th>Pre-spotting Location</th>
<th>X Co-ordinate (m)</th>
<th>Y co-ordinate (m)</th>
<th>Orientation to Desired Path</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>−2 m from Desired Path</td>
<td>10 m from Loading Location</td>
<td>+30° to −10°</td>
</tr>
<tr>
<td>2</td>
<td>Along Desired Path</td>
<td>10 m from Loading Location</td>
<td>+30° to −30°</td>
</tr>
<tr>
<td>3</td>
<td>+2 m from Desired Path</td>
<td>10 m from Loading Location</td>
<td>+10° to −30°</td>
</tr>
<tr>
<td>4</td>
<td>−1 m from Desired Path</td>
<td>6 m from Loading Location</td>
<td>+30° to −10°</td>
</tr>
<tr>
<td>5</td>
<td>+1 m from Desired Path</td>
<td>6 m from Loading Location</td>
<td>+10° to −30°</td>
</tr>
<tr>
<td>6</td>
<td>Along Desired Path</td>
<td>2 m from Loading Location</td>
<td>+20° to −20°</td>
</tr>
</tbody>
</table>

A major design consideration in the auto-spotting system design was the system’s network infrastructure. Excluding the sensors embedded on the RTV, all of the hardware was connected via TCP/IP protocol as this is how the multi-node system is managed by ROS. This was exceptionally useful when designing the system, which has multiple hardware units that communicate through various connections. The auto-spotting design uses two computers, each running modules of code that interface with attached sensors requiring a relatively high rate of communication (10 Hz).

The ROS communication system is based on a subscriber-publisher framework. A module of code or a node within ROS, will subscribe to another node to input data and publish to other nodes to output data. Through this framework, multiple nodes can subscribe to a single node, and a single node can publish multiple data streams or topics to other nodes. The downside to this approach lies in the manner ROS handles the active subscribers and publishers; every subscribed and published topic has to be rooted through the master computer.

To simplify ROS integration, the computer hosting all the systems on the RTV was designated as the “master”. This means that any nodes running on the computer located at the shovel had to be
routed through the computer on the RTV. Unfortunately, this caused great difficulty in communicating via Wi-Fi from the RTV to the shovel. This is not to say that communication would not be possible in a real application, simply that there were implications due to the way ROS is designed. For this reason, in the experiments described in this thesis, the two subsystems were connected via a 50’ Ethernet cord. In the future, the system would be redesigned to allow for wireless communication. For the purposes of testing a LiDAR based UKF, the corded communication setup was deemed sufficient.

5.2 System Development

5.2.1 ROS

Once the MATLAB® simulator was operational, the next step was to convert the developed code into the ROS infrastructure. The algorithms developed in MATLAB® were converted into C++ modules to facilitate integration with ROS. As mentioned previously, ROS acts as a code wrapper, meaning it has built in classes to facilitate code written in the C++ and Python programming languages. While this functionality assisted in porting the system into ROS, a considerable amount of work was required. As the candidate was more experienced with C++ coding, C++ was chosen for this project.

The development process for the RTV implementation was conducted in a similar way to the steps taken in developing the MATLAB® simulator (described in Chapter 4); the kinematic model was first implemented, followed by the estimator and controller. One of the benefits of using ROS is the ability to interchange nodes within the system (see Figure 33). This means that the vehicle block model within the simulator can easily be replaced by a ROS node that handles control inputs and sensor outputs. Thus, the same code running within the ROS simulator ran on the RTV.
The simulated environment developed within ROS was nearly identical to the system developed in MATLAB®. The final result allowed a user to manually operate a simulated kinematic model of the RTV and to initialize an autonomous spotting routine. An example sequence of the RTV spotting along the desired path is shown in Figure 34. The built-in ROS program RVIZ facilitated visualization of the RTV line map and LiDAR ranges.
Figure 34: Auto-Spot sequence visualized in RVIZ
5.2.2 Sensor Integration

Additional work was required to convert the raw RTV sensor outputs into useable data. For instance, the wheel encoder data coming from the Hall effect sensors were registered in ‘tick’ format. A Hall Effect sensor works by sensing whether the induced magnetic field it outputs is occupied by a magnetic material. The sensor is mounted in front of the teeth of a rotating gear (Figure 35). The gear is attached to the axle beside the tire so that as the tire rotates, so does the gear. The Hall Effect sensor registers ticks between each obstruction by each gear tooth. The number of teeth on the gear and the circumference of the tire are known and so the total distance travelled by the tire can be calculated after calibration. Recording the difference in ‘ticks’ registered between a fixed time allows a wheel velocity to be determined.

The SICK LMS 111 LiDAR drivers were previously wrapped in the ROS infrastructure and only required parameter changes to run at higher resolutions; from 1° to 0.5°.

Figure 35: Hall effect sensor mounted to front axle measuring ticks from 80 spoke gear
5.3 Results and Analysis

This section presents the results from the experiments conducted to test the designed and simulated algorithms. The state error was calculated by using the on-board RTK-GPS as ground truth. Note that the RTK-GPS on board the RTV had sub-metre accuracy but is less accurate at lower speeds.

The error plots do not show an estimated error for the vehicle orientation. This is because the Applanix AP 10 GPS system could not calculate a heading (to compare to the estimate) at the low auto-spotting speed.

These error calculations, based on RTK-GPS, were the best possible tool available for evaluating the system’s performance. Final loading locations were also recorded to assist in determining the final positioning performance of the auto-spotting system.

5.3.1 Extended Kalman Filter

The Extended Kalman Filter estimator was tested to compare with the result of the UKF system (see Figure 36). The example depicts a spotting routine when initiated from pre-spotting location #5. The model was able to spot from any location along the desired path as long as the heading error was near zero. If the vehicle was off the path (and thus required orientation alterations to navigate to the path) or initially had large orientation errors, then the resulting spotting location often had a large lateral error. This could be a result of the system model (i.e., filter gains) relying heavily on the vehicle orientation to determine the vehicle position. The EKF estimator design is clearly a viable solution, assuming the GPS measurement is consistently accurate.
5.3.2 Unscented Kalman Filter

The designed auto-spotting system was tested on the RTV from each of the pre-spotting locations to determine whether the system was capable of satisfying the loading requirements. Table 4 lists the final RTV location in relation to the desired loading location (recorded with measuring tape). The average error for the lateral and longitudinal position was 0.13 m and 0.03 m, respectively. Figure 37 demonstrates a spotting action from pre-spotting location #1. From Figure 37 and Table 4, it was demonstrated that the final location was within the loading location criteria (within 1 m and less than 10° of the desired loading location). In fact, over 95% of the experiments conducted (with an initial location in the pre-spot zone) fulfilled the final loading location requirements.
Table 4: Final loading location error for UKF based auto-spotting design

<table>
<thead>
<tr>
<th>Pre-Spotting Location</th>
<th>Orientation</th>
<th>X Distance from Loading Location (m)</th>
<th>Y Distance from Loading Location (m)</th>
<th>Vehicle Orientation from Loading Location (degrees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>+ 30°</td>
<td>+0.6</td>
<td>+0.2</td>
<td>+2°</td>
</tr>
<tr>
<td>1</td>
<td>- 10°</td>
<td>+0.6</td>
<td>-0.6</td>
<td>+5°</td>
</tr>
<tr>
<td>1</td>
<td>0°</td>
<td>-0.1</td>
<td>-0.1</td>
<td>0°</td>
</tr>
<tr>
<td>2</td>
<td>+ 30°</td>
<td>+0.3</td>
<td>-0.5</td>
<td>-2°</td>
</tr>
<tr>
<td>2</td>
<td>- 30°</td>
<td>+0.2</td>
<td>+0.2</td>
<td>+1°</td>
</tr>
<tr>
<td>2</td>
<td>0°</td>
<td>-0.1</td>
<td>-0.2</td>
<td>0°</td>
</tr>
<tr>
<td>3</td>
<td>- 30°</td>
<td>0.6</td>
<td>+0.1</td>
<td>+1°</td>
</tr>
<tr>
<td>3</td>
<td>+ 10°</td>
<td>+0.4</td>
<td>+0.3</td>
<td>+2°</td>
</tr>
<tr>
<td>3</td>
<td>0°</td>
<td>+0.3</td>
<td>0.0</td>
<td>0°</td>
</tr>
<tr>
<td>4</td>
<td>+ 30°</td>
<td>+0.6</td>
<td>+0.2</td>
<td>+1°</td>
</tr>
<tr>
<td>4</td>
<td>- 10°</td>
<td>+0.1</td>
<td>+0.1</td>
<td>+4°</td>
</tr>
<tr>
<td>4</td>
<td>0°</td>
<td>+0.2</td>
<td>+0.2</td>
<td>0°</td>
</tr>
<tr>
<td>5</td>
<td>- 30°</td>
<td>-0.2</td>
<td>+0.4</td>
<td>-2°</td>
</tr>
<tr>
<td>5</td>
<td>+ 10°</td>
<td>+0.9</td>
<td>-0.1</td>
<td>-7°</td>
</tr>
<tr>
<td>5</td>
<td>0°</td>
<td>+0.2</td>
<td>+0.1</td>
<td>0°</td>
</tr>
<tr>
<td>6</td>
<td>+ 20°</td>
<td>+0.3</td>
<td>+0.2</td>
<td>-2°</td>
</tr>
<tr>
<td>6</td>
<td>- 20°</td>
<td>-0.2</td>
<td>+0.1</td>
<td>+3°</td>
</tr>
<tr>
<td>6</td>
<td>0°</td>
<td>0.0</td>
<td>0.0</td>
<td>0°</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>N/A</strong></td>
<td><strong>0.21</strong></td>
<td><strong>0.03</strong></td>
<td><strong>1.1°</strong></td>
</tr>
</tbody>
</table>
Figure 37: Error state plot from Pre-Spot Location #1

The GPS measurement used to calculate the state errors would often drift, making it unusable as a ground truth measurement. Figure 38 plots the calculated error during a spot starting at pre-spot location #2. Re-tracing the estimated RTV location, the latitudinal and longitudinal error never exceeded 0.5 m. This means the large deviations seen in Figure 38 are a result of a poor GPS measurement, not an inaccurate estimate. The GPS measurement does in fact correct itself before the end of the spot. If the GPS measurement were used to estimate the RTV’s location, as it would be in a purely GPS-based system, the estimator would have failed and potentially driven the vehicle into a hazardous situation.
Figure 38: GPS signal roaming during spotting action from Pre-Spot Location #2

The designed auto-spot system was capable of navigating the RTV within close range of the desired loading location when initialized within the desired pre-spot zone. Figure 39 shows the calculated state errors of the RTV when placed well outside (4 m away) the pre-spot zone. The final lateral and longitudinal errors were +0.9 m and -0.2 m, respectively. It was observed that the estimator had difficulty converging on the vehicle orientation with so few initial visible LiDAR ranges.
After several experiments were conducted, the results showed the extent to which the number of visible LiDAR ranges impacts the convergence properties of the estimator. This observation makes sense because the number of visible LiDAR ranges increases the number of comparative points in the ‘a posteriori’ step of the estimator. Figure 40 shows the calculated error states for the RTV spotted from pre-spot location #3 with a resolution of 0.5 degrees instead of the previously used 1 degree resolution. This means, that on average, the number of visible LiDAR ranges on the RTV should double, given that they are initiated with relatively the same pose. This experiment resulted in a loading location error of +0.4 m latitudinal and +0.1 m longitudinal. This result was consistent with other experiments conducted at this resolution and initial error. One interesting observation was how stable the estimator was in this case when compared to
previous experiments. The error trend lines have very few spikes compared to previous experiments.

Additional experiments were conducted at the higher resolution to determine how the system would perform when the vehicle was outside the pre-spot zone (Figure 41). The results were more promising than the previous tested conducted outside the zone. The final latitudinal and longitudinal errors were + 0.6 m and + 0.1 m, respectively. It is clear that increasing the number of visible LiDAR ranges has a significant positive impact on the UKF estimator.

![Figure 40: State error for auto-spot with higher resolution LiDAR](image)

The development of any technology requires multiple iterations to refine and evolve the design. The auto-spot system required multiple improvements before the system was operational. For every successfully acquired data set, there were many showing unsuccessful runs.
One major design challenge that was overcome was the poor results in measuring small angles from the steering encoder, which was used to help estimate vehicle movement. This was a result of a poor relationship between the encoder output and the steering angle when angles were less than eight degrees [40]. This failure had a direct result on estimator performance (Figure 42).

Figure 41: State error for auto-spot test outside pre-spot zone with higher resolution LiDAR

For this reason, the design was altered to use a gyroscope instead. Initially, the measured steering angle was propagated through the system model to determine the vehicle orientation changes (Equation 1). The gyroscope directly measures the rate of change of the vehicle’s orientation therefore the measurement could determine the vehicle orientation changes through numerical integration in the filter (Equation 3). The gyroscope measurements were taken from the built in MEM’s IMU on the Applanix AP-10 (specifications in Appendix A), a floating average over half a second was used to filter the measurement (measured at 10 Hz).
5.4 Discussion

This section discusses the results presented above, in particular the parameters that most significantly influence the performance of the spotting system.

The EKF estimator worked well when the GPS measurement was available and accurate; it is a viable solution when a strong, consistent GPS signal is available.

The UKF estimator worked well when the measurement model registered enough visible ranges from the LiDAR to track the vehicle location and the initial vehicle orientation angle was within the expected range. Within the scope of the experiments conducted for this thesis, it was observed...
that the LiDAR sensor performed more consistently than the GPS, even though the GPS generally had clear visibility of the sky.

The effect of visible LiDAR ranges was observed as a significant factor. As the estimator had more data points to compare, its behaviour was more stable and so its estimate was more accurate. Increasing the LiDAR resolution and thus the quantity of visible ranges proved to be beneficial to the estimator. The effect of increased visible ranges introduced other design considerations. One was the line map profile supplied to the simulated LiDAR sensor. The initial profile used was a rudimentary rectangle with dimensions matching the real RTV. This design was later updated to account for the void in the profile as a result of the RTV’s open cab. As the number of visible points increased, more detail was resolved from the vehicle’s profile, generally resulting in a better estimate of the vehicle orientation.

5.4.1 Error Discussion
A major observation was the effect of poor rotational changes measured by the steering encoder and gyro. Experiments that required large orientation shifts to navigate to the parking path had a larger final latitudinal error. This defect could be resolved by increasing visible LiDAR ranges and a more accurate IMU system.

Testing the RTV in a mine will introduce several elements that will affect the effectiveness of the estimator. Some of these include:

- The accuracy of the wheel encoders will likely degrade as the working surface becomes more irregular. The RTV testing was tested on an old paved pad (Figure 32). The surface was not perfectly flat, but it was certainly not as uneven as the typical surface conditions at a real mine.
The longitudinal error variance was quite low, most likely due to a low vehicle speed and the dynamics of the RTV. The Kubota RTV engine resists motion when the throttle is removed. The controller in the experiments described herein applied a zero throttle full brake signal once the estimated location was less than one metre from the loading location. Future renditions should account for vehicle speed and momentum as the vehicle nears the loading location. Without this, the vehicle could over shoot the desired loading location.

Weather conditions may affect the effectiveness of the onboard sensors; specifically the LiDAR. As mentioned previously, wet and dusty environments have a negative impact on LiDAR effectiveness.
Chapter 6 Conclusions

6.1 Conclusions
The problem studied in the work presented in this thesis pertains to the feasibility of autonomously spotting a haul truck without the use of GPS. Industry partners have suggested a move towards GPS-less based solutions because GPS has proven to be unreliable in many mining environments. This research began with a field study on current haul truck spotting effectiveness at the Barrick Goldstrike open pit mine. There it was learned that, on average, 9% of all spotting actions required a corrective action.

To study this problem further, a haul truck simulator was developed in MATLAB® (and later in ROS) to facilitate the design, development and implementation of a GPS-less, LiDAR-based UKF estimator. This was done by using a predictive estimate of the vehicle’s pose based on haul truck odometry that was then fused with a corrective estimate from a shovel mounted LiDAR. The developed estimation and control algorithms were verified using both simulation and real world tests. Real world tests were performed on an automation-ready Kubota RTV 900. Results showed that LiDAR-based UKF estimation is a strong candidate for vehicle pose estimation of haul trucks during spotting. An additional benefit to this research was the development of a framework for implementing estimation and control systems on the Kubota RTV 900.

A considerable amount of time and effort went into this study and the development of the auto-spot system concept. Listed below are some additional conclusions and lessons learned about the development of an effective auto-spotting system:
• An applied system should be deployed in phases with an emphasis on spot-assist in the earlier stages.

• An auto-spotting solution could not only decrease spotting times but also increase the percentage of double-sided loading.

• Vehicle pose estimation (using a LiDAR based UKF) is possible on slow moving vehicles when there are as few as 10 to 20 visible ranges.

• The optimal loading location of a haul truck should, by default, be based on the orientation of the shovel and working face. If possible, the location should be designated by the shovel operator.

• There are several spotting configurations that are used to accommodate pit conditions. The main configuration modelled in this report was a frontal cut with single-sided loading. An auto-spotting system will require flexibility to accommodate these variations.

• Further research should be conducted to weigh the advantages and disadvantages of a shovel mounted versus a vehicle mounted LiDAR estimator. This thesis suggests the use of a shovel-mounted LiDAR.

• Spot time variability and its effect on overall cycle times were identified as an area of improvement at multiple mining operations (Section 2.2).

• It is important to develop a system in strategic phases, testing the model, then the estimator, then the controller. This ensures that one module is working correctly before integrating the next.

• The autonomous Clearpath Kubota RTV is a practical tool for researchers looking for a development platform to build control and navigation systems for mining equipment. ROS is an excellent platform for developing an environment to simulate and test these autonomous solutions.
6.2 Future Steps
If pursued further, the next step for this research would be to work on the robustness of the auto-spot design. An operational framework that satisfies the reliability and safety requirements of autonomous equipment in an open pit mine will need to be developed. The consistent successful operation of an automated system is of the utmost importance; otherwise it will not be used in favour of manual operations.

Additional areas of work stemming from the topics raised during the research described in this thesis are discussed below.

6.2.1 Additional Sensors
As was mentioned in the analysis of the RTV auto-spot experiments, a potential solution to improving the state estimation of a vehicle would be to add an additional sensor to the corrective update. The obvious addition would be a GPS. While this addition would go against the intended design of the system, if used properly, it could benefit systems in mining environments where signals are strong and readings have demonstrated accuracy. The downside to this method would be the false readings that can occur when satellites go out of range. Putting a threshold on the compared states, in order to automatically remove erroneous GPS outputs, could mitigate this problem.

Another deficiency mentioned was the noisy readings coming from the gyroscope. To combat this, a more accurate sensor could simply be used to better estimate the rotation of the vehicle. This was merely a problem with the hardware used, and would not affect a real deployment.
6.2.2 Rotating Platform

An important factor missing from the experiments conducted in this research is the effect of the shovel’s rotation. Often a shovel will be loading another haul truck or cleaning up the face when a haul truck enters the pit to be loaded. The LiDAR sensors could be mounted on the bottom half of the shovel that does not rotate during operation, however, there would be difficulties in finding an appropriate mounting location and concerns regarding build-up of material on the underside. A more suitable long term solution would be to model the movement of the shovel swing into the vehicle state estimator. This could be done by monitoring the rate of rotation of the shovel’s upper-half via an absolute encoder on the pivot column. Another option would be to interpret the shovel rotation based on the heading calculation from a high precision GPS. HPGPS systems are often installed on shovels to monitor the dip of the advance. As it was mentioned earlier in this text, various mining authorities are more interested in a GPS-less solution.

6.2.3 LiDAR Improvements

As was mentioned in the analysis of the RTV auto-spot experiments, estimation accuracy was heavily impacted on the number of visible range values. It was seen that as the number of visible range values was increased so too was the accuracy and stability of the estimator. The obvious solution is to upgrade the LiDAR to a higher resolution unit. While this will increase the number of visible points, a more beneficial solution would be to use a three dimensional LiDAR. This would significantly increase the number of visible data points and improve scan matching performance. With a 3D LiDAR, scan matching is performed on multiple levels instead of just one with a 2D sensor.

3D LiDAR sensors are significantly more expensive, though most autonomous vehicles with commercialization in mind deploy a high frequency 3D LiDAR, such as the Google car’s Velodyne sensor that is to be fitted on Caterpillar’s fleet of autonomous haul trucks [41]. There
are downsides to using a 3D sensor. For instance, they increase the complexity of the estimation process and therefore the computational burden. This could limit the closed loop frequency and degrade system performance.

Another area of study for future work related to LiDAR performance is the effect of increased vehicle profile detail on estimator proficiency. The UKF algorithm will perform differently as the scan matching algorithm changes. More detailed line maps could have a positive effect when a sufficient LiDAR resolution is available and negative effects when not.

6.2.4 Standardized Framework

It was mentioned in Section 3.1.2, that maintaining a consistent data format across subsystems would be essential for system integration. This becomes even more important when multiple vehicles from different suppliers are integrated into the system e.g., Kutamsu 930E haul trucks working beside CAT D11 dozers. Having a consistent data format is common practice in many industries, though mining equipment providers often supply a fleet of equipment so it would be impractical for them to accommodate their systems for competitors. In the past, this attitude has been to the detriment of mining authorities that purchase equipment from several different suppliers. Fortunately, in the last decade several companies came together to develop IREDES (International Rock Excavation Data Exchange Standard). It is a potential industry standard for transferring data between mining equipment to site computer systems for data acquisition [42]. It utilizes XML to define system profiles that can be classified into standardized formats. This permits new adopters to integrate their system to use IREDES quite easily. It is suggested that any application of an auto-spotting system use a standard, such as IREDES, to accommodate multi-machine integration.
6.2.5 Maintenance
Mine equipment designs are required to account for the varying environmental conditions the vehicles will experience. Equipment needs to be robust enough to handle rain, sleet, snow and sand storm conditions not to mention intense sunlight. Ensuring sensors will operate under these conditions is a constant challenge for instrumentation suppliers. The Ingress Protection Rating (IP code) classifies the grade of protection an instrument has against the intrusion of foreign objects. An IP 67 rated unit is dust tight and safe to operate in wet conditions (submersible to 1m). This rating would be suitable for most, if not all, mining environments. That’s not to say that a sensor will perform well in this environment, only that it will not incur damage. There are numerous LiDAR products available with an IP 67 rating that would suit the needs of an auto-spotting system. Though technology relying heavily on the consistent operation of a LiDAR would require extensive testing to ensure the instruments availability would meet the needs of its design. Nevertheless, it is fair to suggest that a proper maintenance schedule would have to be upheld to maintain operation to fix inevitable conditions such as the ‘caking’ of dirt, mud and snow to a sensor. A maintenance schedule similar to that of a backup camera installed on a haul truck would be suitable.

6.2.6 Environmental Conditions
The first question that should always be asked when installing a sensor in a mining environment is whether it can operate in dense particulate environments. Multiple studies [28] [29] [43] have been conducted on the effect of particulates on LiDAR measurements. Many have conflicting results, often because the intended use of the sensor varies dramatically. The success of a deployed LiDAR will vary depending on the rubric to which it is being measured; tracking a vehicle the size of a small house or generating detailed geophysical data. It has been cited numerous times in this report that LiDAR sensors are being deployed on mobile vehicles for the purpose of environment mapping. Often those deployments are for obstacle avoidance and
detection such as Zhu, Church and Larie’s report on LiDAR use during helicopter landing in brownout/whiteout conditions [43]. Their OPAL sensor was successful in filtering out snow cloud particulates from obstacles or ground targets. These types of sensors would be of great importance in insuring the consistent operation of an auto-spotting system during dusty or rainy mining conditions.

6.2.7 Dynamic Model

The current design uses kinematic equations to define the motion of the RTV. In practice, a more accurate model could be defined by including the dynamics of the system. This might include the servo control of the throttle, brake and steering and inherent inertial effects due to the weight of the RTV. While the kinematic model was sufficient in controlling the vehicle at low speeds, the ability of the system to respond appropriately at high speeds would be depleted. The model presented in this thesis also assumes that there is no slip between the tire and ground surface.
List of References


http://www.komatsu.com/ce/currenttopics/v09212/index.html


http://www.cs.brown.edu/people/tld/courses/cs148/02/sonar.html


[47] Honeywell, "SMART Position Sensor, 75 mm and 225 mm Linear Configurations," Sensing
and Control, Golden Valley, MN, Data Sheet 2010.


## Appendix A Instrument Specifications

### Sick LMS 111

<table>
<thead>
<tr>
<th>Functional data</th>
<th>Minimum</th>
<th>Typical</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scan angle</td>
<td></td>
<td></td>
<td>270°</td>
</tr>
<tr>
<td>Scanning frequency</td>
<td>25 Hz</td>
<td></td>
<td>50 Hz</td>
</tr>
<tr>
<td>Remission</td>
<td>10%</td>
<td></td>
<td>Several 1,000%1) (reflectors)</td>
</tr>
<tr>
<td>Angular resolution</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>With 25 Hz</td>
<td>0.25°</td>
<td>0.5°</td>
<td></td>
</tr>
<tr>
<td>With 50 Hz</td>
<td></td>
<td>0.5°</td>
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</tr>
<tr>
<td>Measuring error 1. Reflected pulse2)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Systematic error</td>
<td>±30 mm (1.18 in)</td>
<td>±50 mm (1.97 in)</td>
<td></td>
</tr>
<tr>
<td>Temperature drift</td>
<td>0 mm/°C (0 in/°F)</td>
<td>0.32 mm/°C (0.01 in/°F)</td>
<td></td>
</tr>
<tr>
<td>Statistical error (1 σ)</td>
<td>12 mm (0.47 in)</td>
<td>20 mm (0.79 in)</td>
<td></td>
</tr>
<tr>
<td>Immunity to external light</td>
<td></td>
<td></td>
<td>40 klx</td>
</tr>
<tr>
<td>Evenness of the scan field (25 Hz)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cone</td>
<td>±0.5°</td>
<td>±1°</td>
<td></td>
</tr>
<tr>
<td>Inclination</td>
<td>±1°</td>
<td>±2°</td>
<td></td>
</tr>
<tr>
<td>Distance from mirror axis of rotation (zero point on the X and Y axis) to the rear of the device</td>
<td>55 mm (2.17 in)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 43: Data Sheet for Sick LMS 111 [44]
Trimble AP10 GNSS-Inertial OEM System

**Figure 44:** Expected error from Trimble AP10 GNSS-Inertial OEM System [45]

<table>
<thead>
<tr>
<th>PERFORMANCE SPECIFICATIONS</th>
<th>(RMS ERROR)</th>
</tr>
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<tr>
<td>Terrestrial Applications, (DMI required)</td>
<td></td>
</tr>
<tr>
<td>System Accuracy - Full GNSS Availability</td>
<td></td>
</tr>
<tr>
<td>Real time Correction Source</td>
<td>Horizontal Accuracy (RMS)</td>
</tr>
<tr>
<td>Omnistar XP</td>
<td>0.25 m</td>
</tr>
<tr>
<td>Omnistar VBS</td>
<td>1.00 m</td>
</tr>
</tbody>
</table>

| System Accuracy - 20 second outage |             |
| Real time Correction Source | Horizontal Accuracy (RMS) | Heading Accuracy (RMS) |
| Omnistar XP | 2.00 m | 0.50 deg |
| Omnistar VBS | 2.50 m | 0.55 deg |

| System Accuracy - 60 second outage |             |
| Real time Correction Source | Horizontal Accuracy (RMS) | Heading Accuracy (RMS) |
| Omnistar XP | 9.0 m | 0.90 deg |
| Omnistar VBS | 10.0 m | 1.00 deg |

1 Typical performance. Actual results are dependent upon satellite configuration, atmospheric conditions and other environmental effects. System requires heading initialization procedure.

**Figure 45:** Data Sheet for Trimble AP10 GNSS-Inertial OEM System [45]

**TECHNICAL SPECIFICATIONS**
- Advanced Applanix IN-Fusion™ GNSS-Inertial integration technology
- Advanced Trimble Maxwell® 6 Custom GNSS survey technology (two chipsets)
- 220 Channels: (per chipset)
  - GPS: L1 C/A, L2C, L2E (Trimble method for tracking unencrypted) L5
  - GLONASS: L1 C/A and unencrypted P code, L2 C/A and unencrypted P code, L3 CDMA
  - GALILEO: L1 CBOC, E5A, E5B, E5AltBOC
  - QZSS: L1 C/A, L1C, L1 SAIF, L2C, L5, LEX11
  - SBAS: L1 C/A (EGNOS/MSAS), L1 C/A and L5 (WAAS)
    - L Band: OmnistAR VBS, HP, XP and G2
- High precision multiple correlator for GNSS pseudorange measurements
- Unfiltered, unsmeared pseudorange measurements data for low noise, low multipath error, low time domain correlation and high dynamic response
- Very low noise GNSS carrier phase measurements with <1 mm precision in 1 Hz bandwidth
- Proven Trimble low elevation tracking technology
- Support for optional Distance Measurement Indicator (DMI) input
- Support for optional GNSS Azimuth Measurement System (GAMS™)
- Support for optional POSPac Mobile Mapping Suite post-processing software
### ADIS 16362 Six Degrees of Freedom Inertial Sensor

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Test Conditions/Comments</th>
<th>Min</th>
<th>Typ</th>
<th>Max</th>
<th>Unit</th>
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<td><strong>GYROSCOPES</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dynamic Range</td>
<td>Dynamic range = ±300°/sec</td>
<td>±300</td>
<td>±300</td>
<td>±300</td>
<td>°/sec</td>
</tr>
<tr>
<td>Initial Sensitivity</td>
<td>Dynamic range = ±150°/sec</td>
<td>0.0495</td>
<td>0.0505</td>
<td>0.0505</td>
<td>°/sec/LSB</td>
</tr>
<tr>
<td>Sensitivity Temperature Coefficient</td>
<td>−20°C ≤ T ≤ +70°C</td>
<td>±0.0125</td>
<td>±0.0125</td>
<td>±0.0125</td>
<td>°/sec/LSB</td>
</tr>
<tr>
<td>Misalignment</td>
<td>Axis-to-axis</td>
<td>±0.05</td>
<td>±0.05</td>
<td>±0.05</td>
<td>Degrees</td>
</tr>
<tr>
<td>Nonlinearity</td>
<td>Best fit straight line</td>
<td>±0.47</td>
<td>±0.47</td>
<td>±0.47</td>
<td>% of FS</td>
</tr>
<tr>
<td>In-Run Bias Stability</td>
<td>1 °, SMPL_PRD = 0x0001</td>
<td>±ε</td>
<td>±ε</td>
<td>±ε</td>
<td>°/sec</td>
</tr>
<tr>
<td>Angular Random Walk</td>
<td>1 °, SMPL_PRD = 0x0001</td>
<td>±0.05</td>
<td>±0.05</td>
<td>±0.05</td>
<td>°/sec</td>
</tr>
<tr>
<td>Bias Temperature Coefficient</td>
<td>−20°C ≤ T ≤ +70°C</td>
<td>±0.01</td>
<td>±0.01</td>
<td>±0.01</td>
<td>°/sec/°C</td>
</tr>
<tr>
<td>Linear Acceleration Effect on Bias</td>
<td>Any axis, 1 ° (MSC_CTRL[7] = 1)</td>
<td>±0.05</td>
<td>±0.05</td>
<td>±0.05</td>
<td>°/sec/g</td>
</tr>
<tr>
<td>Bias Voltage Sensitivity</td>
<td>VCC = 4.75 V to 5.25 V</td>
<td>±0.3</td>
<td>±0.3</td>
<td>±0.3</td>
<td>°/sec/V</td>
</tr>
<tr>
<td>Output Noise</td>
<td>±300°/sec range, no filtering</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>°/sec rms</td>
</tr>
<tr>
<td>Rate Noise Density</td>
<td>f = 25 Hz, ±300°/sec range, no filtering</td>
<td>0.044</td>
<td>0.044</td>
<td>0.044</td>
<td>°/sec/Hz rms</td>
</tr>
<tr>
<td>3 dB Noise Bandwidth</td>
<td></td>
<td>330</td>
<td>330</td>
<td>330</td>
<td>Hz</td>
</tr>
<tr>
<td>Sensor Resonant Frequency</td>
<td></td>
<td>14.5</td>
<td>14.5</td>
<td>14.5</td>
<td>kHz</td>
</tr>
<tr>
<td>Self-Test Change in Output Response</td>
<td>±300°/sec range setting</td>
<td>±696</td>
<td>±1400</td>
<td>±2449</td>
<td>LSB</td>
</tr>
</tbody>
</table>

| **ACCELEROMETERS**                     |                                                       |     |     |      |        |
| Dynamic Range                          | Each axis                                            | ±1.7 | ±1.7 | ±1.7 | g      |
| Initial Sensitivity                    |                                                       | 0.330 | 0.330 | 0.330 | mg/LSB |
| Sensitivity Temperature Coefficient    | −20°C ≤ T ≤ +70°C                                     | 40 | 40 | 40 | ppm/°C |
| Misalignment                           | Axis-to-axis                                         | ±0.2 | ±0.2 | ±0.2 | Degrees |
| Nonlinearity                           | Best fit straight line                                | ±0.1 | ±0.1 | ±0.1 | % of FS |
| In-Run Bias Error                      | ±1 °                                                 | 6 | 6 | 6 | mg |
| In-Run Bias Stability                  | 1 °                                                  | 41 | 41 | 41 | μg |
| Velocity Random Walk                   | 1 °                                                  | 0.09 | 0.09 | 0.09 | °/sec/°hr |
| Bias Temperature Coefficient           | −20°C ≤ T ≤ +70°C                                     | ±0.05 | ±0.05 | ±0.05 | °/sec/°C |
| Bias Voltage Sensitivity               | VCC = 4.75 V to 5.25 V                                | ±2.5 | ±2.5 | ±2.5 | mg/V |
| Output Noise                           | No filtering                                         | 5 | 5 | 5 | mg rms |
| Noise Density                          | No filtering                                         | 0.23 | 0.23 | 0.23 | mg/°Hz rms |
| 3 dB Bandwidth                         |                                                       | 330 | 330 | 330 | Hz |
| Sensor Resonant Frequency              |                                                       | 5.5 | 5.5 | 5.5 | kHz |
| Self-Test Change in Output Response    | X-axis and y-axis                                    | 505 | 505 | 505 | LSB |

Figure 46: Datasheet for ADIS 16362 IMU [46]
## Honeywell SMART Position Sensor Linear Configuration

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Component</th>
<th>Parameter 75 mm</th>
<th>Parameter 225 mm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>sensor</td>
<td>Analog (SPS-L075-HALS)</td>
<td>Analog (SPS-L225-HALS)</td>
</tr>
<tr>
<td>Sensing range</td>
<td>only</td>
<td>0 mm to 75 mm [0 in to 3.0 in]</td>
<td>0 mm to 225 mm [0 in to 8.86 in]</td>
</tr>
<tr>
<td>Resolution</td>
<td>0.05 mm [0.002 in]</td>
<td>0.14 mm [0.00055 in]</td>
<td>0.0035 mm [0.000137 in]</td>
</tr>
<tr>
<td>Supply voltage</td>
<td>6 Vdc to 24 Vdc</td>
<td>34 mA max.</td>
<td>88 mA max.</td>
</tr>
<tr>
<td>Output</td>
<td>0 Vdc to 5 Vdc</td>
<td>19.76 mV/mm typ.</td>
<td>282.16 counts/mm typ.</td>
</tr>
<tr>
<td>Supply current</td>
<td></td>
<td>400 µs</td>
<td>57.6 kbit/s</td>
</tr>
<tr>
<td>Linearity</td>
<td></td>
<td>30 ms</td>
<td>30 ms</td>
</tr>
<tr>
<td>Reverse polarity</td>
<td></td>
<td>26.4 V at 175 °C [575 °F]</td>
<td>+0.4% full scale output</td>
</tr>
<tr>
<td>Sensitivity</td>
<td></td>
<td>400 ms</td>
<td>3200 µs</td>
</tr>
<tr>
<td>Update rate</td>
<td></td>
<td>400 µs</td>
<td>3200 µs</td>
</tr>
<tr>
<td>Baud rate</td>
<td></td>
<td>30 ms</td>
<td>30 ms</td>
</tr>
<tr>
<td>Initial startup time</td>
<td></td>
<td>flying leads: red = supply voltage, black = ground, green = output</td>
<td></td>
</tr>
<tr>
<td>Termination</td>
<td></td>
<td>40 mm [1.6 in] min.</td>
<td>20 G from 10 Hz to 2000 Hz</td>
</tr>
<tr>
<td>Cable bend radius</td>
<td></td>
<td>-40 °C to 125 °C [-40 °F to 257 °F]</td>
<td>-40 °C to 150 °C [-40 °F to 302 °F]</td>
</tr>
<tr>
<td>Storage temperature</td>
<td></td>
<td>20 G from 10 Hz to 2000 Hz</td>
<td>20 G from 10 Hz to 2000 Hz</td>
</tr>
<tr>
<td>Air gap</td>
<td></td>
<td>20 G from 10 Hz to 2000 Hz</td>
<td>20 G from 10 Hz to 2000 Hz</td>
</tr>
<tr>
<td>Sealing</td>
<td></td>
<td>20 G from 10 Hz to 2000 Hz</td>
<td>20 G from 10 Hz to 2000 Hz</td>
</tr>
<tr>
<td>Shock</td>
<td></td>
<td>20 G from 10 Hz to 2000 Hz</td>
<td>20 G from 10 Hz to 2000 Hz</td>
</tr>
<tr>
<td>Vibration</td>
<td></td>
<td>20 G from 10 Hz to 2000 Hz</td>
<td>20 G from 10 Hz to 2000 Hz</td>
</tr>
<tr>
<td>Housing material</td>
<td></td>
<td>20 G from 10 Hz to 2000 Hz</td>
<td>20 G from 10 Hz to 2000 Hz</td>
</tr>
<tr>
<td>Approvals</td>
<td></td>
<td>20 G from 10 Hz to 2000 Hz</td>
<td>20 G from 10 Hz to 2000 Hz</td>
</tr>
<tr>
<td>Mounting: screws</td>
<td>sensor and magnet actuator</td>
<td>20 G from 10 Hz to 2000 Hz</td>
<td>20 G from 10 Hz to 2000 Hz</td>
</tr>
<tr>
<td>Strength</td>
<td></td>
<td>20 G from 10 Hz to 2000 Hz</td>
<td>20 G from 10 Hz to 2000 Hz</td>
</tr>
</tbody>
</table>

Notes:
- Percent linearity is the quotient of the measured output deviation from the best fit line at the measured temperature to the full scale output span.

Figure 47: Data sheet for contactless absolute encoder made by Honeywell (SPS-L225-HALS)

## Cherry Geartooth Speed Sensor

<table>
<thead>
<tr>
<th>Operating Voltage Range</th>
<th>5 - 24 VDC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supply Voltage</td>
<td>24 - 30 VDC</td>
</tr>
<tr>
<td>Supply Current</td>
<td>6 mA max</td>
</tr>
<tr>
<td>Output Saturation Voltage</td>
<td>400 mV max</td>
</tr>
<tr>
<td>Output Current</td>
<td>20 mA max</td>
</tr>
<tr>
<td>Operating Temperature</td>
<td>-40° to +125°C (GS100502 &amp; GS100701) -40° to +105°C (GS100501)</td>
</tr>
<tr>
<td>Storage Temperature Range</td>
<td>-40° to +125°C (GS100502 &amp; GS100701) -40° to +105°C (GS100501)</td>
</tr>
<tr>
<td>Output Rise time</td>
<td>5µS</td>
</tr>
<tr>
<td>Output Fall time</td>
<td>5µS</td>
</tr>
<tr>
<td>Electrostatic Discharge Immunity</td>
<td>+ 3kV indirect contact, + 4kV direct contact</td>
</tr>
<tr>
<td>Electric Field Radiated Immunity</td>
<td>At 10V/m (using 30% amplitude modulation @ 1kHz) from 26MHz to 1000 MHz</td>
</tr>
<tr>
<td>Electrical Fast Transient Test</td>
<td>+ 2kV on DC power supply</td>
</tr>
<tr>
<td>Immunity to Magnetic Fields</td>
<td>SAE J113-22 (600 microT AC field; 5Hz to 2kHz, 2mT &amp; 1mT DC field)</td>
</tr>
<tr>
<td>Conducted Immunity Test</td>
<td>Injected with 10Vrms from 150kHz to 80 MHz</td>
</tr>
<tr>
<td>Dielectric Withstand Voltage</td>
<td>MIL-STD-202F, Method 301, 1000V applied for a minimum of one minute.</td>
</tr>
<tr>
<td>Insulation Resistance</td>
<td>MIL-STD-202F, Method 302, Test Condition B 500V applied for one minute.</td>
</tr>
</tbody>
</table>

Figure 48: Data sheet for magnetic sensor made by Cherry (GS100502)