A FIELD STUDY ON LIDAR SENSOR LASER SIGNAL AND SURROUNDING OBJECT RELATIONSHIP FOR UNMANNED GROUND VEHICLE IN PRECISION AGRICULTURE

A Thesis
Submitted to the Graduate Faculty
of the
North Dakota State University
of Agriculture and Applied Science

By

Breeya Pederson

In Partial Fulfillment of the Requirements
for the Degree of
MASTER OF SCIENCE

Major Department:
Agricultural and Biosystems Engineering

April 2022

Fargo, North Dakota

North Dakota State University
Graduate School

Title

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

MASTER OF SCIENCE

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ABSTRACT

LiDAR sensor's mapping and detection abilities make these sensors an important tool for research on navigation and object detection for robots and vehicles. This study used a ground robot and LiDAR sensor to collect navigational data sets from North Dakota State University Research Extension Center agricultural test plots in Carrington, ND. Three different height and angle combinations were used to study the factors that could potentially affect object detection. Three trials were run for each sensor placement and recorded the distance the laser pulse traveled and the intensity of the laser. The analysis results showed that the data did not have a normal distribution. However, statistical analysis showed a relationship between the return intensity of the laser pulse from the sensor and the distance the object was from the sensor. Thus, this study showed that LiDAR sensors could be a navigation tool for UGV applications in precision agriculture.

ACKNOWLEDGMENTS

I would like to thank my advisor, Dr. Xin Sun, for his guidance through this process and Dr. Thomas Bon for his support and help over the last 3 years. I would also like to thank Dr. Umamaheswara Rao Tida, Dr. Cengiz Koparan, and the faculty and staff of the NDSU ABEN Department for their support and guidance through this project.

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1. INTRODUCTION

1.1. Purpose of Study

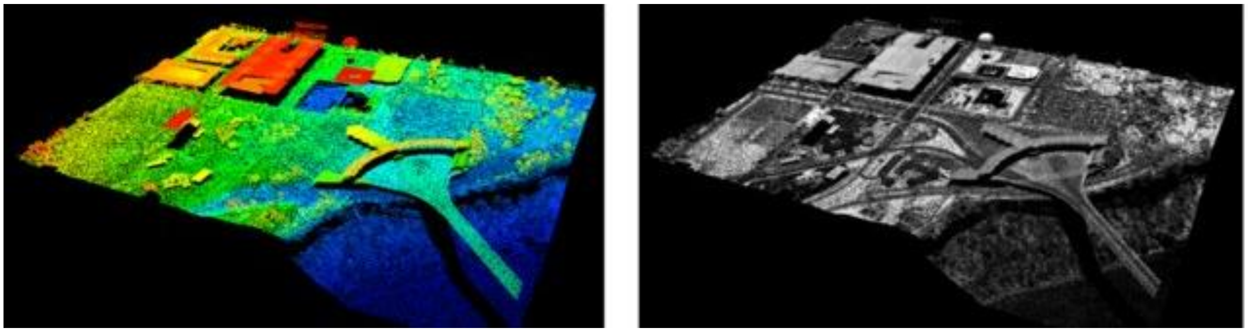
North Dakota State University has been continuously growing the Precision Agriculture Program since its creation in 2019. The program team members conduct research on various topics, from weed identification to drone imaging. The research done with autonomous or unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs) has greatly expanded with the addition of the LiDAR sensor. LiDAR, or light detection and ranging, is a widely used sensor and has been applied to many industries such as autonomous vehicles. LiDAR sensors work by emitting pulses of light that reflect off surrounding objects (Teague). The sensors then use the return time from the laser to calculate the distance, X, Y, and Z coordinates, intensity, time, and other variables. Using a LiDAR sensor gives an advanced approach to autonomous vehicles, whether with road vehicles or agricultural machinery. Understanding more about a LiDAR sensor's signal can allow for more progress or efficacy while using them in real-world applications. This study investigated the relationship between the distance that a laser pulse, emitted from a LiDAR sensor, travels to a surrounding object and the return intensity of that laser pulse. More can be determined about optimal sensor placement using the relationship between these two variables.

1.2. Background of Research Topic

Autonomous vehicles have become an increasingly relevant part of research in agriculture. Companies such as Tesla, Ford, John Deere, and Case IH, have been researching and releasing new autonomous technology, which has increased the need to continue learning about autonomous machinery. Both the automotive industry and agricultural sector utilize this technology and have allowed more opportunities for continuing research. Machinery that can run effectively, efficiently, and autonomously means that more work can be achieved with less input. In agriculture, autonomous machinery means crop production could be increased with the same amount of work input. It also makes expanding a farming operation much more feasible because less labor is needed to get the same amount of work done.

There are many similarities to what the agricultural sector and the automotive industry are doing in terms of autonomous vehicles. Both industries utilize similar base concepts for what the autonomous machine needs. For each case, sensors to detect the machine's surroundings, such as LiDAR sensors, cameras, and GPS, are necessary for the machine to be able to navigate safely and effectively. In cars, obstacle detection and avoidance features are one of the main safety priorities for the passengers who would be buying these cars. The safety features are also important to the other cars in the roadway and any pedestrians in the area (What is an Autonomous Car?). In contrast, most agricultural machinery does not include passengers. Therefore, the safety features of an autonomous vehicle in agriculture are very different because the surrounding people are the top safety priority. However, obstacle avoidance and other safety features are still extremely relevant in the agriculture field.

As mentioned above, LiDAR sensors provide information about distances from obstacles and people through emitting pulses of light that reflect off surrounding objects (Teague) and then calculating the distance, X, Y, Z coordinates, intensity, and time. LiDAR then creates a 3D point cloud of surrounding objects using those variables to have both the 3D graphical output as well as a numerical data set for each frame. The image below shows a comparison of what a LiDAR sensor output looks like compared to the actual topography shown on the right side. This comparison helps illustrate what a LiDAR sensor shows the user when it is running.



(a) (b)

Figure 1.1. (a) LiDAR sensor output. (b) Actual image of the topography (Lohani & Ghosh).

Because the sensor can relay surrounding objects in real-time, it is widely utilized in autonomous technologies. LiDAR sensors are ideal for the safety features that are needed for autonomous vehicles but have many other applications. Some of the other popular uses of LiDAR sensors include crop and weed detection as well as topography mapping.

Features such as real-time obstacle detection make LiDAR sensors an excellent candidate for many different uses and in different industries. Expanding upon what is currently known about LiDAR sensors is another way to continue learning about the technology. Building upon its current capabilities in autonomous vehicles, in conjunction with the other uses in agriculture, allows for a better machine with fewer sensor inputs needed to achieve similar results. The obstacle detection needed for the safety of autonomous vehicles and the plant identification abilities studied in the agricultural field can both be achieved with the same sensor, making it important to know as much as possible about how these sensors work.

1.3. Objectives of Study

The goals of this study were to increase the understanding of LiDAR sensors by analyzing the relationship between the return intensity from laser pulses emitted from the sensor and the distance traveled by the laser beam. This study focused on the return intensity of the laser pulse emitted by the LiDAR sensor and analyzed the relationship between that variable and the distance that laser pulse travels to a surrounding object. Multiple forms of statistical analysis were conducted to represent the relationship between a surrounding object and the laser pulse that came out from the LiDAR sensor.

1.3.1. Sub Objectives

- Collect LiDAR sensor output data from field testing with the remote-controlled agricultural robot.
- Run statistical analysis on the collected LiDAR sensor data.
- Determine the type of relationship between the return intensity of a laser pulse and the distance from the LiDAR sensor to the object

1.4. Research Approach

A variety of crops and weeds were planted at a satellite research site for North Dakota State University in Carrington, North Dakota. The field was utilized for a variety of studies including this data collection. A remote-controlled robot with a LiDAR sensor attached to the front at varying heights and angles was used to collect the data sets. Three trial positions were used for the sensor height and angle, named Condition 1, 2, and 3, each with a specific height and angle. Each condition consisted of 3 trials, in which the robot was directed from one end of the field to the other end directly above a double row of crops spaced 30 inches from each other. The collected data sets were then statistically analyzed to determine the relationship between 2 of the calculated variables.

1.5. Organization of Thesis

This thesis investigated the function of LiDAR sensors in a precision agriculture field robot, why the relationship between the distance traveled and the return intensity of the laser is important, and the results of statistical analysis on these data sets. Chapter 1 explores this relationship to help build a better understanding of sensor placement depending on the output required for different experiments. Chapter 2 contains a literature review that discussed ground robots in agriculture, the navigation of ground vehicles in both agriculture and the automotive industry, LiDAR sensors, and how it relates to this study. The method of data collection and materials used are discussed in Chapter 3. Chapter 4 then addresses the relationship between the return intensity of the laser and the distance from the sensor to the object and a comparison of statistical methods was used to determine the best predictor model. Lastly, Chapter 5 concludes the paper with a discussion of the results.

2. REVIEW OF LITERATURE

2.1. Ground Robots in Precision Agriculture

Precision agriculture is a continuously growing field. There have been many advancements in the field of ground robots in particular. The robots created in precision agriculture serve many purposes. Ground robots in agriculture are being created to reduce the most time-consuming and labor-intensive processes. Crop seeding is one of these tasks as this process is very meticulous for farmers. Therefore, designing a robot to complete this task would greatly reduce the time and energy needed for this task (Azmi, et. al.). The figure below shows examples of robot prototypes built for crop seeding.

(a) (b)

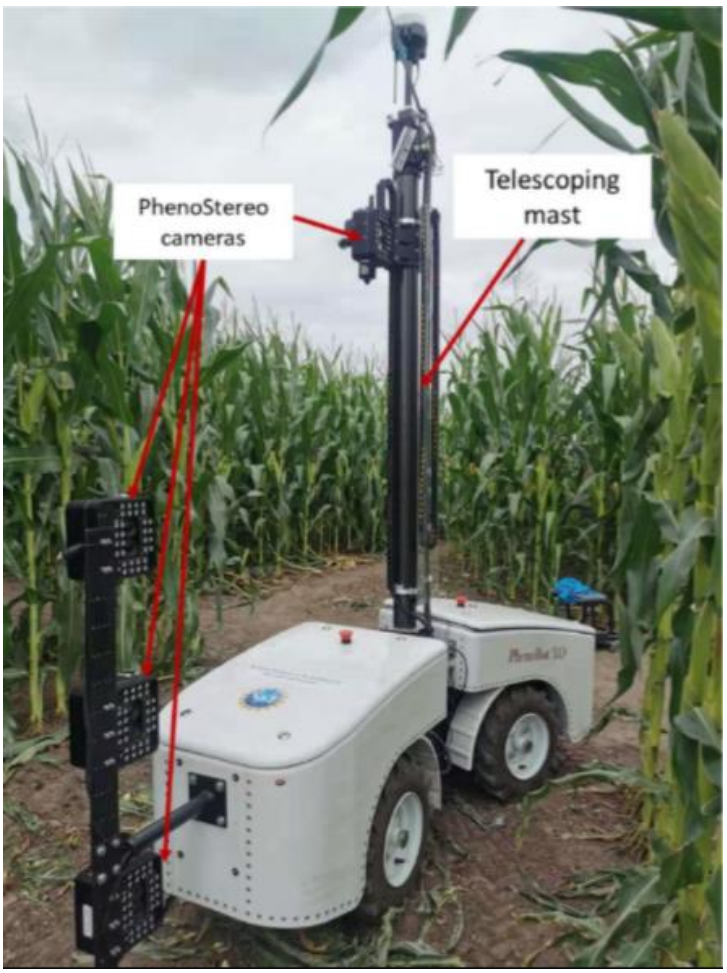
Figure 2.1. Prototype crop seeding robots created for precision agriculture research (a) Azmi, et. al. (2021) (b) Kumar and Ashok (2021).

Both robots designed by Azmi et al. (2021) and Kumar and Ashok (2021) were designed to reduce the amount of time it takes for farmers to sow seeds. Spraying is another task that could be easily completed with a ground robot. A robotic spraying platform that was built to reduce costs and increase autonomy using solar panels and a completely electric system was effectively able to reach and focus on the plants to collect thermal data (Loukatos et al.). While the spraying capabilities of this research are still in progress, the concept is there. Mechanical weeding is another way to achieve the same goal. There have been robotic concepts in that research area, such as a concept created by Quan et al. (2022) that had both high crop and weed detection and an 85.91% removal rate with very low crop damage recorded. The sprayer concept and mechanical weeding concept are shown in Figure 2.2.

(a) (b)

Figure 2.2. (a) Robotic sprayer concept (Loukatos, et al.) (b) Mechanical weeding concept (Quan et al.).

The concepts by both Loukatos et al. (2021) and Quan et al. (2022) have been successful in their advancement, proving that both concepts have great future possibilities for future improvement. A study conducted in Bavaria, Germany determined that farmers are more likely to consider owning smaller ground robots rather than larger autonomous tractors. The interest in small robots for agriculture, especially for smaller farms, is high (Spykman, et al.). The reduction of labor costs and increased efficiency of using robots for agriculture procedures is why they have become such a large part of current research (Gai, et. al.). Creating a robot that can manually or autonomously complete tasks, such as the concepts above, can greatly reduce labor costs, and allow farmers to accomplish more in the same amount of time. Figure 2.3. is the prototype agricultural robot used in the study conducted by Gai et al. (2021) to help develop better navigation for agricultural ground robots. Research by both Gai et al. (2021) and Weiss and Biber (2011) have been working towards the same goal to create a localization or mapping system that can help agricultural robots navigate. By mapping the details of a field and its rows, ground robots will be more able to work effectively in field conditions. They need a localization or vehicle positioning system when conducting any of the previously mentioned tasks ground robots are being built for. Mapping is an important step for agricultural ground robots to be successful and has been continuously improving for many years. Figure 2.3. also shows the test robot used by Weiss and Biber (2011) to conduct their 3D laser sensor mapping.



(a)

Figure 2.3. (a) Agricultural ground robot working on improving navigation (Gai et al.) (b) Test robot using a 3D laser sensor to create plant map (Weiss and Biber).

(b)

Figure 2.3. (a) Agricultural ground robot working on improving navigation (Gai et al.) (b) Test robot using a 3D laser sensor to create plant map (Weiss and Biber) (continued).

Along with agricultural ground robots being created for a single purpose, some robots are being created as a base that can be altered for any agricultural application. Grimstad and From (2017) created Thorvald II, a reconfigurable robot that can be used in a variety of agricultural settings.

Figure 2.4. Thorvald II robot in standard configuration (Grimstad and From).

Thorvald II can be utilized for greenhouse settings, orchards, and typical crop fields. The versatility of the base concept makes it applicable for many different types of use. Because of the versatility in the use of these ground robots, another important factor to consider is the control system. Whether the robot is manually or autonomously controlled, there still needs to be a detailed control system in place to prevent any issues with the robot. A study done by Tu et al. (2019) designed a robot that used 2 steering modes with corresponding controllers. It was able to follow straight and curved paths well with smooth transitions along the curves. All agricultural ground robots need to be able to cleanly follow the paths they are given when being used in a field operation to prevent damage to the crops. Improving the controls of the robot can achieve this and continue improving the research.

Completing tasks more efficiently is one of the main priorities of robots in agriculture but another important aspect that robots can help in is tracking purposes. Robotics and the autonomy of agriculture machinery allow for better regulation of field data. Transmitting data in real-time about the condition of the crop and its health allows for better and more efficient care (Baerdemaeker). The ability to consistently know the condition of the soil in a field or the moisture content in the plant's leaves means the field can be taken care of to the best of the farmers' ability. Along with reducing costs, the time a task takes, and the labor needed, getting the field the best care possible is extremely important. Ground robots are an increasingly important research topic to continue to improve the output of farms.

2.2. LiDAR Sensors

LiDAR sensors are widely used across a variety of industries and in many types of research. Since LiDAR's creation in the 1960s, it has been utilized for projects ranging from aiding meteorologists to mapping the bottom of the ocean (Wandinger). In both research and industry, LiDAR sensors have been expanding upon work previously done using multiple types of sensors. Minimizing the number of sensors needed eliminates the need for extremely complex control systems and allows for a simpler system. The simplicity and versatility of LiDAR sensors are why they have become a large part of many research fields.

2.2.1. Components of LiDAR Sensors

LiDAR sensors are comprised of a laser scanner, high precision clock, GPS, inertial navigation measurement unit or IMU, and a data storage/management system. Depending on the type of sensor, the components may vary. However, all LiDAR sensors have some form of the previously mentioned components (*Light Detection and Ranging (LiDAR)*). The laser scanner component of a LiDAR sensor projects the laser pulses emitted from the sensor and measures the angle at which it was fired. The scanner then receives the reflected pulse from the surface of the sensor which is the return. The intensity of the return is based on a scale of 0-256. It is based on the light energy reflected from the object the laser pulse returned from. Different material types influence the return intensity, some of which are listed in the table below.

Table 2.1. Reflectivity (%) of various materials (Song, et. al).

Materials	Reflectivity (%)
White paper	Up to 100
Dimension lumber	94
Snow	80-90
Beer foam	88
White masonry	85
Limestone, clay	Up to 75
Newspaper with print	69
Tissue paper, with ply	60
Deciduous trees	Typ. 60
Carbonate sand (dry)	57
Beach sands	Typ. 50
Carbonate sand (wet)	41
Coniferous trees	Typ. 30
Rough wood pallet (clean)	25
Concrete, smooth	24
Asphalt with pebbles	17
Lava	8
Black rubber tire wall	2

The effect of the material on the return intensity is an important factor of this research as return intensity is one of the variables being analyzed. The clock used in a LiDAR sensor is another important component as it records the time it takes for the laser pulse to return which can be used in the calculation of other variables such as the distance the object is from the sensor which is the other primary variable analyzed in this study. Therefore, the calculation of the 2 variables, return intensity and distance, is crucial to this research.

Other components, such as the GPS in a LiDAR sensor are not always necessary but can be used to determine the positioning of the sensor. This along with the IMU, which measures the orientation of the sensor to the ground, are good references for data collection using LiDAR sensors. However, the last component listed above is one of the most important. The data storage/management system of a LiDAR sensor allows for data to be collected and recorded for data analysis. Without those systems, LiDAR sensors would not have the same capabilities for research as they do. Therefore, this is one of the most important characteristics of LiDAR sensors.

2.2.2. Current Uses of LiDAR Sensors

The uses of LiDAR sensors range from autonomous navigation to predicting weather patterns. The versatility in uses makes LiDAR sensors applicable to a range of different types of research and in many industries. As mentioned previously, one of the uses of LiDAR sensors is mapping. The figure below shows a LiDAR sensor output for a topography map.

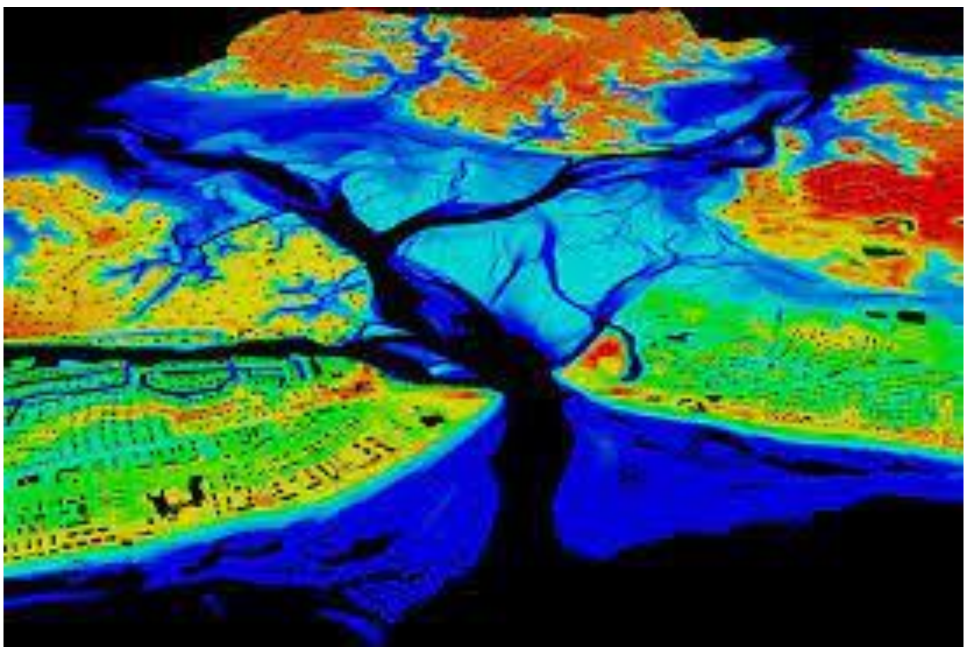


Figure 2.5. Topography map created using LiDAR sensor (US Department of Commerce).

Topography mapping is currently one of the larger uses of these sensors and this benefit is applied in many industries. Agriculture, forestry, urban planning, and many other sectors can all benefit from the maps created by LiDAR sensors. Archeologists can utilize these maps when analyzing historical sites, and a study on geomorphology was able to use a t-LiDAR to analyze structural changes in bedrock (Wiatr, et. al.). Taking LiDAR images of large areas allows the output map created to be analyzed and anomalies in the map can be detected. A study conducted by Wang and Glenn (2009) used airborne LiDAR data to create a method of getting a bare-earth digital terrain model (DTM) with less error than previous studies. By creating DTMs with less error, other areas of study can use them to determine other factors with more accuracy. For example, another study by Casana et al. (2021) on archaeological landscapes conducted in Hawaii, Colorado, and New Hampshire, found that they were able to find archaeological site locations by taking LiDAR images of large areas and eliminating the tree canopy and vegetation to look at the bare-earth terrain or DTM. Another way that LiDAR sensors can be utilized for mapping is depicted in the figure below that shows a backpack created by apple maps, that is carried around to advance their system.

Figure 2.6. Apple maps backpack created to update their maps.

Apple Maps vans have been using LiDAR sensors to collect accurate street-level data in recent years. Currently, they have expanded their research to using LiDAR sensors, GPS, and cameras on a backpack to make their new maps update even more accurate.

Another popular use of LiDAR sensors is in the autonomous vehicle sector. As mentioned previously, this is a key part of multiple industries, the automotive and agricultural sectors being the largest. A LiDAR sensor's ability to detect obstacles, both moving and stationary, and relay that information back to the control system in real-time makes it unparalleled in its benefits to autonomous machines. This is a feature that makes it useful to many other industries, such as meteorology and hazard assessment (The history of LiDAR). Both uses require detecting the sensor's surroundings to detect objects around the sensor or movement in the sensor's surroundings.

2.2.3. Agricultural Uses of LiDAR Sensors

The current research using LiDAR in agriculture primarily focuses on the ability to identify plants using the sensor as well as its use in obstacle detection. Plant identification, as well as field mapping, are the most widely researched topics for LiDAR in agriculture. One study conducted using LiDAR focused on identifying weeds between rows of different crops. By mounting a LiDAR sensor above the crop height on an ATV, they were able to distinguish between the crop and the weeds based on height from 4 varieties of crops (Andújar, et. al.). Other studies, such as the work by Abanay et al. (2022), use LiDAR to create a calibration method to keep an agricultural robot on its path to conduct its tasks.

Agricultural robots are not only able to complete plant identification or mapping tasks but also require mapped areas for autonomous work. A mapping and localization system is essential for agricultural robots as they are working in large areas to keep track of where they are (Le, et.

al.). This is important to note because of how relevant it is in agriculture specifically. A ground robot may be in an isolated area with limited distinguished land markers and therefore needs to create its localization system based on the field. The figure below shows the robot and LiDAR sensor used for mapping in the study conducted by Le et al.

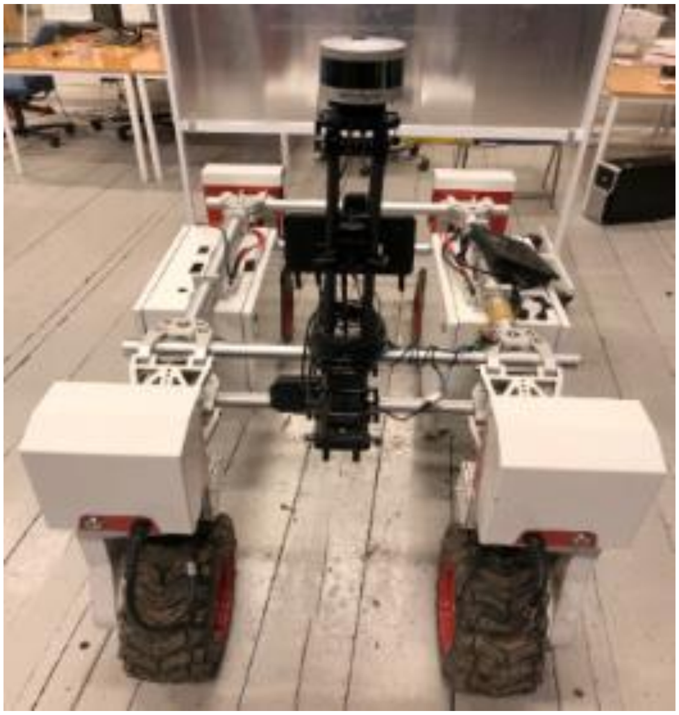


Figure 2.7. Agricultural robot and LiDAR sensor for localization system mapping (Le, et al.).

Mapping is something that can be achieved by using a LiDAR sensor, but it is also something an autonomous robot using a LiDAR sensor would require in agriculture. The information gathered by the forestry sector and through land mapping analyzes the relationship between different variables in some work.

In agriculture, few papers include the relationship between the return intensity of a laser and the distance between the sensor and object. A study on how the distance between the sensor and object affected the return intensity of the laser beam was conducted. They found a primarily linear relationship between the distance and intensity (Tatoglu and Pochiraju, 2012) similar to what

Bordin et al. (2013) determined in a study comparing the distance and output intensity data in a forestry setting. LiDAR research focuses on its ability to detect obstacles and its ability to create 2D or 3D maps. There are a limited number of studies like the previous that discuss the relationship between the return intensity and distance, especially in agriculture. In the most current research, LiDAR sensors have mostly been analyzed in urban or city settings. Agriculture has a variety of different characteristics to consider when using a LiDAR sensor that urban settings do not need to be concerned with (Le, et. al.). That is why understanding how an agricultural setting will affect the output of the sensor is important.

2.3. Navigation of Autonomous Ground Vehicles

2.3.1. Background

Autonomous vehicles are becoming more and more popular in the modern automobile industry. The concept of the self-driving car has been around since the 1500s when Leonardo Da Vinci invented his concept for a self-propelled cart. Since the creation of modern vehicles, the introduction of Autopilot to Tesla vehicles in 2015 has helped bring the idea of a fully autonomous car closer to reality. Figure 2.8. shows a variety of sensors that Tesla uses for their autonomous features in the Autopilot controls. Cameras surround the vehicle to detect objects close to the vehicle as well as ultrasonics right around the car.

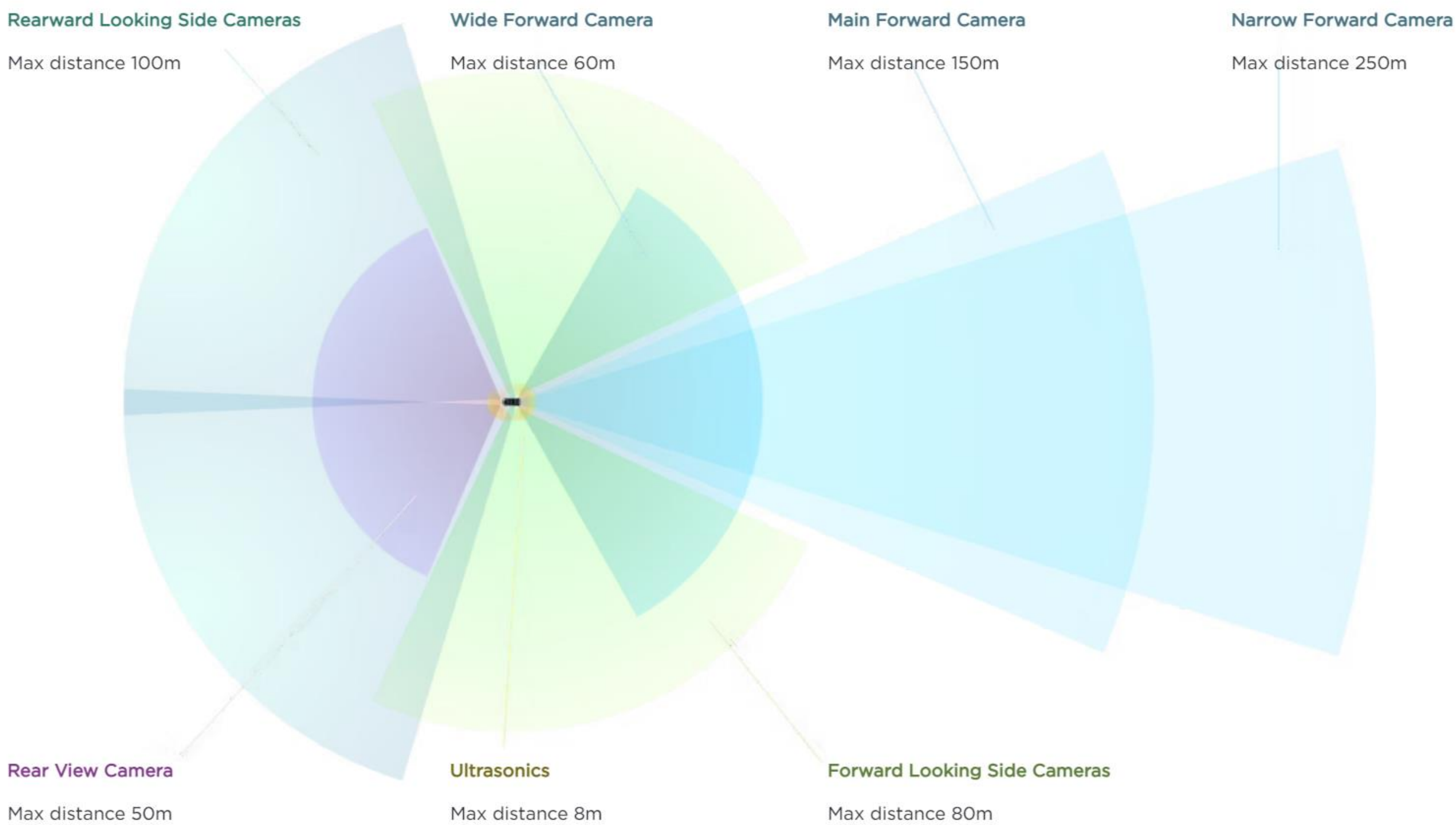


Figure 2.8. Sensors and capabilities used in Tesla Autopilot (Autopilot).

In agriculture, autonomous vehicles are becoming one of the top researched areas for machinery companies. For instance, Case IH released a concept for an autonomous tractor in 2016 and has continued to consider this a realistic option for farmers with large operations to add to their machinery. John Deere is another company that has an autonomous tractor that will be available for large-scale production by late 2022. Companies like these have created concepts that use this technology to improve their machine's capabilities and ease of use. Below are examples of both Case IH's and John Deere's autonomous tractor prototype.

(a)

Figure 2.9. (a) Case IH Autonomous tractor (Case IH autonomous concept vehicle) (b) John Deere Autonomous tractor (John Deere).

(b)

Figure 2.9 (a) Case IH Autonomous tractor (Case IH autonomous concept vehicle) (b) John Deere Autonomous tractor (John Deere) (continued).

Whether in the automobile industry or the agriculture field, to make the autonomous function works, a variety of sensors are needed on the vehicle such as GPS, RTK, LiDAR, and cameras to navigate as well as a sophisticated control system and machine learning to make decisions (Figure 2.10.). Each of these sensors is integral to the operation of an autonomous machine and is each very complex in what they accomplish. Because of the complexity, there are concerns about how safe and effective the machines are (Lokshina, et. al.). The safety concerns for both industries guide much of the research on this technology. However, each industry has different safety concerns and technical obstacles to overcome.

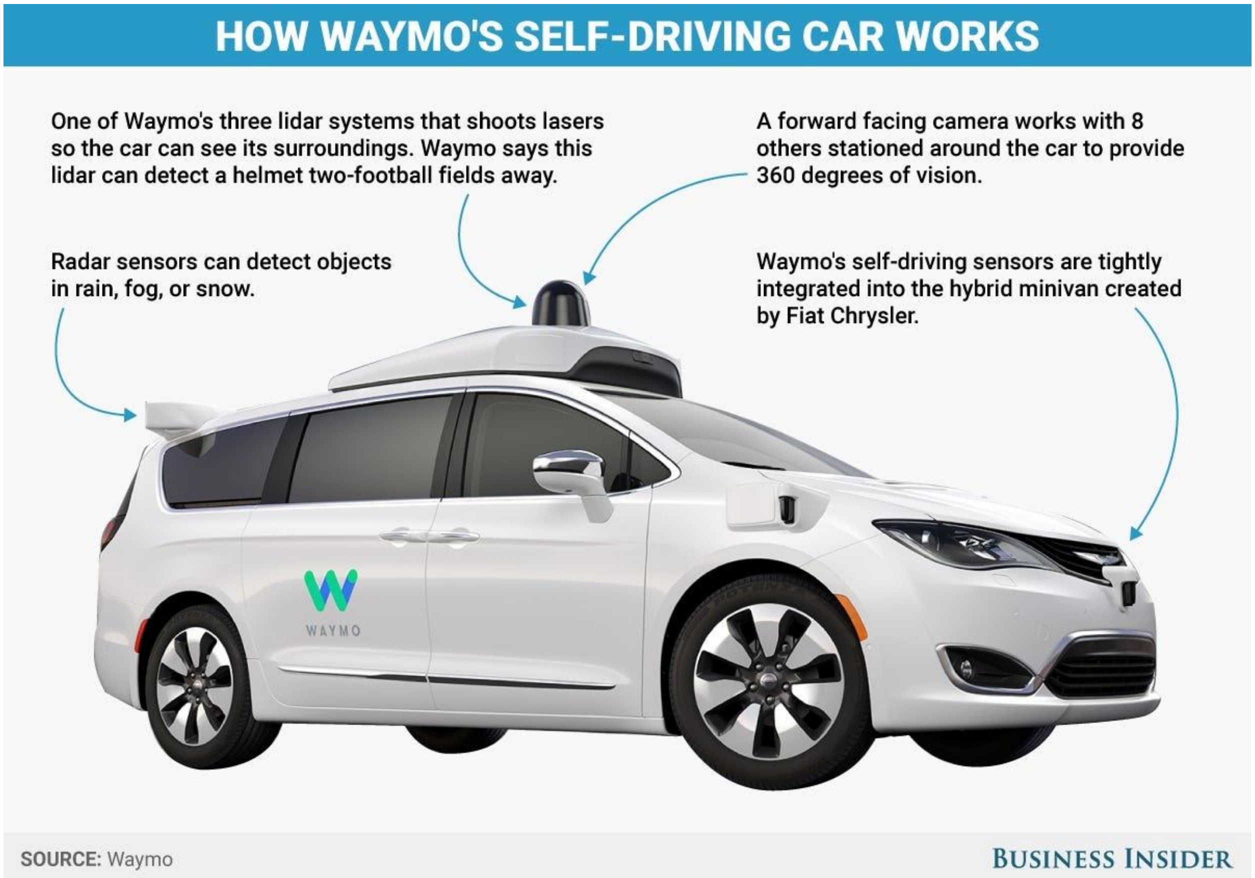


Figure 2.10. Waymo's self-driving car sensor set up (Why lidar is doomed).

2.3.2. Automobiles

Autonomous vehicles require more measures to be taken regarding public safety compared to agricultural machinery. The safety features are extremely important to self-driving vehicles being a viable option for transport. For instance, LiDAR sensors are installed on the autonomous to make sure all the objects around autonomous vehicles are scanned and identified. The image below shows a LiDAR sensor being used for an autonomous vehicle.

Figure 2.11. Example of LiDAR sensor about of cars surroundings (Allyh).

As illustrated, the sensor output shows the people and cars surrounding the sensor. This is one of the most important aspects of an autonomous machine – detecting surrounding objects. The safety of the surrounding people is important to the advancement of autonomous cars, as they are being created to improve driving safety. The automobile industry has more to overcome in terms of public trust than the technology behind autonomous vehicles (Kim, et. al.). As stated, the technology behind autonomous cars is less of a concern than getting the public to consider buying an autonomous vehicle. Distrust in technology is prevalent due to the buyers' need to be able to trust autonomous driving technology with their life. Many socioeconomic factors have been studied that influence an individual's thoughts on autonomous vehicles (Lokshina, et. al.). Studying these factors allows companies to understand how the public will receive an autonomous car and how it can be marketed. Overall, more built-in safety features and more complex decision-making capabilities are needed in cars than in agricultural machinery.

The machine learning needed for cars is extremely complex. It needs to be able to determine the safest course of action in millions of scenarios. There are many considerations to include, such as road traffic and conditions, that are constantly changing. Therefore, the deep learning system needs to be able to take in information and problem solve based on that in real-time (Zhu, et. al.). Being able to adapt to the constantly changing environment is an important aspect of being able to utilize autonomous functions in a road vehicle. Without complex decision-making algorithms, machines may not be able to make the necessary decisions to keep people safe. However, each company interprets these concerns differently depending on their priorities which is part of the public trust concerns that automotive companies need to deal with when presenting the public with autonomous vehicles. The concerns brought up in the studies done by Kim et al. (2022), Lokshina et al. (2022), and Zhu et al. (2022) as well as additional safety concerns are a large obstacle for autonomous vehicles to overcome. However, they differ from the concerns that autonomous agricultural machines face.

2.3.3. Agricultural Machinery and LiDAR Sensors

The use of LiDAR sensors has become synonymous with autonomous vehicles. The ability to detect moving and stationary obstacles and relay that information back to the controls of a system is key to why these sensors are used in place of a range of other sensors for navigation purposes. An autonomous agricultural robot using only LiDAR-based navigation was studied by Malavazi et al. (2018) to determine if one sensor would be adequate for navigation. The abilities in navigation and obstacle avoidance that LiDAR sensors can give to agricultural machinery open many more possibilities for effective and efficient work. Research conducted from 1990 to 2018 at Hokkaido University was analyzed in a case study. Through the university's research on 13 autonomous agriculture vehicle concepts, they determined that laser scanners are more accurate than cameras at longer distances (Roshanianfard, et al.). That better accuracy makes LiDAR one of the most important sensors on an autonomous machine. A study focusing on the design and validation of a fully autonomous tillage tractor was conducted by Jeon et al. (2021) to determine the coverage efficiency. They were able to determine that the proposed planner system provided an increase in coverage efficiency providing positive results those autonomous vehicles can be highly effective.

However, there are a variety of concerns that differ for agricultural machines than for cars. An autonomous tractor typically will not be carrying passengers or dealing with traffic patterns and road conditions. Other factors must be considered such as the cost of running a fully autonomous field tractor. One study did find that the cost of running an autonomous BED system had costs comparable to or lower than a one or two-manned diesel vehicle annually (Lagnelov, et. al.). Running costs are important to consider as the goal of this technology is to reduce labor but also reduce costs. Another consideration for this technology is the energy source as it can be an added cost or limit to the technology. When the autonomous vehicle needs to be refueled or charged needs to be planned for in advance. The source, whether a chargeable battery or fuel, is a factor that needs to be considered as it does with autonomous cars. Renewable energy sources being used in agricultural machinery have not been previously explored the same way is has for cars. A recent study by Ghobadpour et al. (2019), discussed the benefits of using vehicle electrification for autonomous agricultural machines as it has the advantage of flexibility in control and would be able to be built into the already existing autonomous controls.

Another difference between cars and agricultural machinery is that charging stations/gas stations are easily accessible along the roadway for cars. Agricultural vehicles need to plan in more detail when, where, and how they are going to recharge or refuel. With fuel, the robot can be sent to a location where a truck can be waiting to fill it. But to be recharged, the robot would either need sites set up or be able to hold a charge for the time it is in the field. Considering fueling/recharging options is important to determine how to design a fully autonomous agricultural machine.

Along with the need for reasonable costs and adequate fuel, understanding field conditions and the limitations of the machines is important. There will always be varying conditions in an agricultural setting and there is a possibility of a machine getting stuck. So, while road conditions and traffic patterns are not a consideration, the quality of the field and the risk to the machine are. However, understanding when to use an autonomous machine is similar to understanding when the conditions are not adequate for a manually operated machine. This means, there should be adequate conditions and a plan to repair the autonomous tractor should any issues arise. With those plans in place, an autonomous tractor would be a way for farmers to save labor on certain tasks.

2.4. Conclusion

Precision agriculture is continuously growing and becoming integral to how farms function. Ground robots are one aspect of precision agriculture that has been expanding especially in research. The ability to complete the same task, with less labor input and time means farms can dedicate fewer people to doing simple work in the field. Autonomous vehicles – automobiles and agricultural machines – both contribute to this as well. There can be fewer people doing the same amount of work which can allow for better care in more fields. These technologies will all contribute to the efficiency of the farm and help improve productivity.

Current research covers the use of LiDAR sensors in a variety of settings, both in agriculture and other research areas. However, the relationships between different components and the use of those in sensor placement are not well researched at this current time. The ability to understand how the components affect each other allows for a better understanding of the best placement and use of a LiDAR sensor. There has been a limited amount of research into the relationship between return intensity and distance in past work. The previous research on this topic has not been within an agricultural-focused field. Using a data set from field research will obtain more applicable data for agricultural use and understanding this relationship is important when using LiDAR for future experiments. This relationship if proven will be helpful to consider when determining sensor placement for plant detection or other research when the return image needs to be clear.

The research about the return intensity to the LiDAR is a good basis for what this paper will continue exploring. Especially in agriculture, there is little research into how the distance affects the return intensity of the laser. The components that are detected and calculated using LiDAR sensors are what the focus of this research is. The relationship between 2 components – the intensity of the laser when it returns to the sensor and the distance the laser traveled to the object it is detecting. This relationship if proven will be helpful to consider when determining sensor placement for plant detection or other research when the return image needs to be clear.

3. MATERIALS AND METHOD

3.1. Field Environment

The data sets for this study were collected at North Dakota State University's Carrington Research Extension Center (REC) located in Carrington, North Dakota. This site focuses on crop production practices, soil health and improvement, and new agricultural technologies evaluation. The test plot used at Carrington REC consisted of a variety of crops and weeds planted in rows for a variety of research projects, including drone imaging, weed identification, and autonomous machinery research. Figures 3.1. and 3.2. show the test plot and machine used in Carrington, ND for data collection.

Figure 3.1. NDSU Carrington Research Extension Center fields.

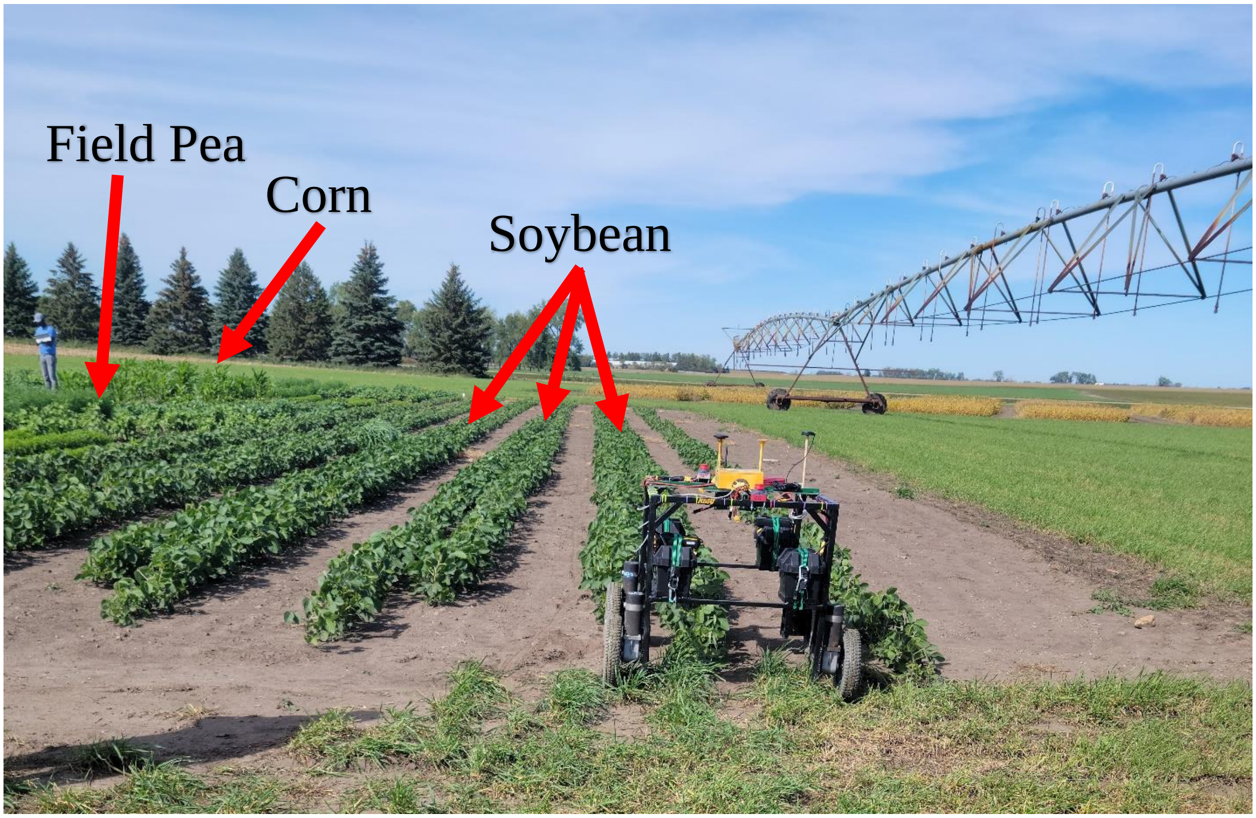


Figure 3.2. Mini Weedbot at NDSU Carrington REC for field testing - Sept. 2021.

This study was run on a single row on the test plot. Each row consisted of 4 types of crops in varied orders. The row used in this study consisted of field pea, lentil, flax, and dry bean, set up with weeds in the center of each row as illustrated in Figure 3.3. below.

Field Pea	Field Pea	HORSE.S	Field Pea	Field Pea	Sugarbee	Sugarbee	RRPW.S	Sugarbee	Sugarbee
Field Pea	Field Pea		Field Pea	Field Pea	Sugarbee	Sugarbee	HORSE.S	Sugarbee	Sugarbee
Field Pea	Field Pea	WATER.S	Field Pea	Field Pea	Sugarbee	Sugarbee	RAG.R	Sugarbee	Sugarbee
Field Pea	Field Pea	HORSE.R	Field Pea	Field Pea	Sugarbee	Sugarbee	RRPW.R	Sugarbee	Sugarbee
Field Pea	Field Pea	KOCH.R	Field Pea	Field Pea	Sugarbee	Sugarbee	RAG.S	Sugarbee	Sugarbee
Field Pea	Field Pea	KOCH.S	Field Pea	Field Pea	Sugarbee	Sugarbee	KOCH.R	Sugarbee	Sugarbee
Field Pea	Field Pea	RRPW.S	Field Pea	Field Pea	Sugarbee	Sugarbee		Sugarbee	Sugarbee
Field Pea	Field Pea	RRPW.R	Field Pea	Field Pea	Sugarbee	Sugarbee	WATER.R	Sugarbee	Sugarbee
Field Pea	Field Pea	WATER.R	Field Pea	Field Pea	Sugarbee	Sugarbee	HORSE.R	Sugarbee	Sugarbee
Field Pea	Field Pea		Field Pea	Field Pea	Sugarbee	Sugarbee	WATER.S	Sugarbee	Sugarbee
Field Pea	Field Pea	RAG.R	Field Pea	Field Pea	Sugarbee	Sugarbee	KOCH.S	Sugarbee	Sugarbee
Field Pea	Field Pea	RAG.S	Field Pea	Field Pea	Sugarbee	Sugarbee		Sugarbee	Sugarbee

Flax	Flax	WATER.R	Flax	Flax	Lentil	Lentil	RRPW.S	Lentil	Lentil
Flax	Flax	HORSE.R	Flax	Flax	Lentil	Lentil	HORSE.S	Lentil	Lentil
Flax	Flax		Flax	Flax	Lentil	Lentil		Lentil	Lentil
Flax	Flax	KOCH.R	Flax	Flax	Lentil	Lentil	KOCH.S	Lentil	Lentil
Flax	Flax	KOCH.S	Flax	Flax	Lentil	Lentil	HORSE.R	Lentil	Lentil
Flax	Flax	HORSE.S	Flax	Flax	Lentil	Lentil	RAG.R	Lentil	Lentil
Flax	Flax		Flax	Flax	Lentil	Lentil	RRPW.R	Lentil	Lentil
Flax	Flax	RAG.S	Flax	Flax	Lentil	Lentil	KOCH.R	Lentil	Lentil
Flax	Flax	RRPW.R	Flax	Flax	Lentil	Lentil	WATER.R	Lentil	Lentil
Flax	Flax	RAG.R	Flax	Flax	Lentil	Lentil	RAG.S	Lentil	Lentil
Flax	Flax	WATER.S	Flax	Flax	Lentil	Lentil	WATER.S	Lentil	Lentil
Flax	Flax	RRPW.S	Flax	Flax	Lentil	Lentil		Lentil	Lentil

Figure 3.3. Experimental setup of each row created by Dr. Xin Sun's PAG team.

The conditions of this experiment were kept as uniform as possible. This includes the use of one row for each trial that was completed. The weather factors were also kept consistent to limit the possible effect on the data. Each trial was completed on a sunny day with minimal clouds. The temperature range was also consistent, ranging from 65°F - 80°F with wind from 26 mph to 36 mph. The pace of the robot was another factor that was kept as uniform as possible. Each trial consisted of 1400 – 2200 frames of data. The variables, such as temperature, wind, and sun/cloud coverage, were not taken into consideration when modeling and analyzing this data set. Due to that, the experiment was conducted to minimize the effect of any of these factors on the results.

3.2. LiDAR Sensor

The sensor used for data collection was a Velodyne LiDAR - 32vlcp or Ultra Puck. This LiDAR sensor has a 200-meter detection range with high accuracy. The sensor can see its surroundings with a 360° horizontal view and a 40° vertical view. With a 903 nm wavelength laser utilized in the laser scanner component of this LiDAR, the laser can see through many weather conditions, including fog, rain, and snow. This sensor was attached at different heights and angles on the front of the robot used to get different samples to test. The sensor shown below in Figure 3.4. is the Velodyne Ultra Puck (VLP-32C). This sensor was utilized in this study to collect information about the surroundings in a research field. The microprocessor attached to the sensor was hooked up to the laptop and the data was recorded in Veloview, which is free software provided by Velodyne that is compatible with Velodyne LiDAR sensors.

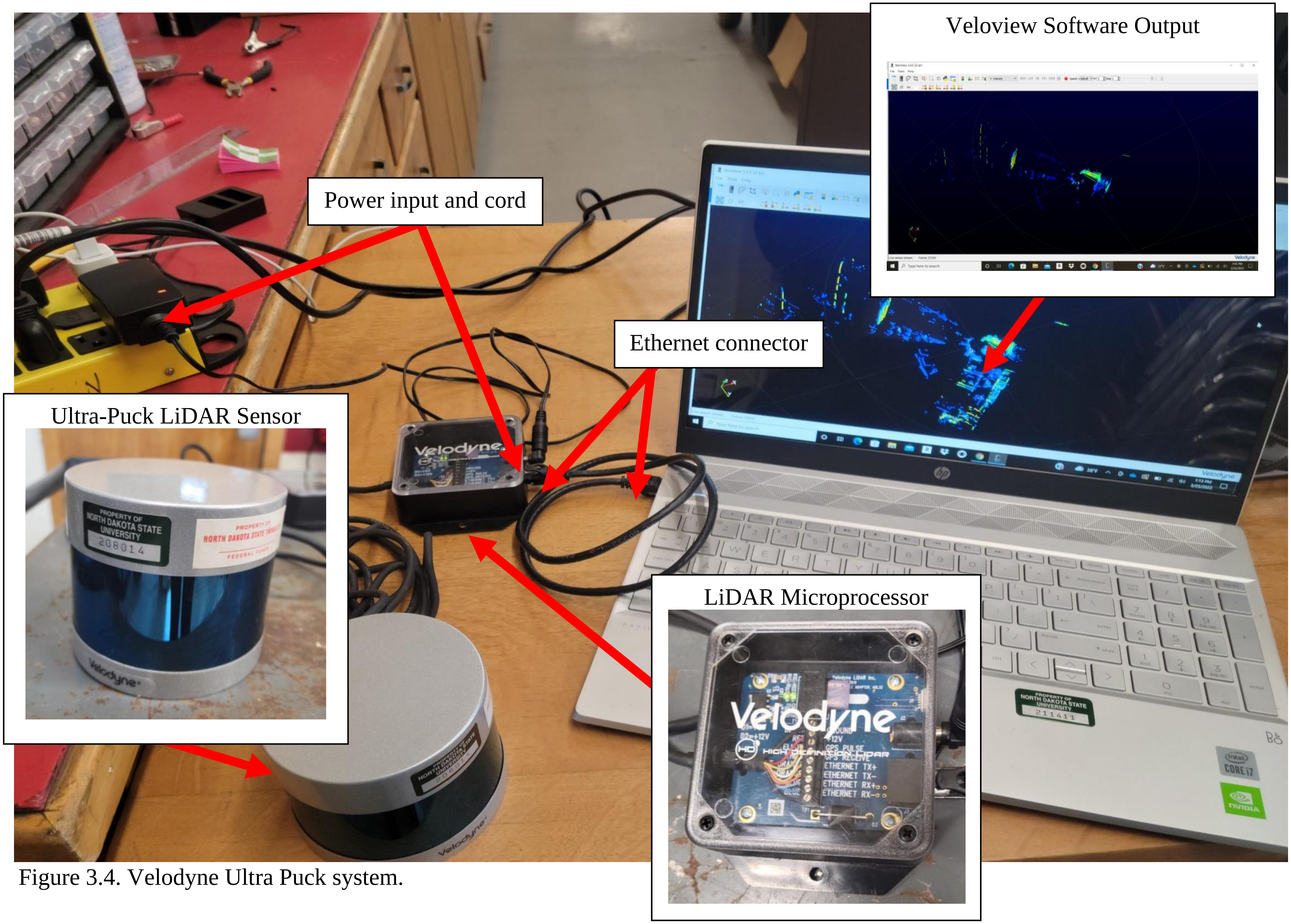


Figure 3.4. Velodyne Ultra Puck system.

The LiDAR sensor was mounted to the precision agriculture robot used for the experiment. In Creo Parametric 4.0, a LiDAR mounting system was developed. The mounting system needed to be able to attach to 2 different size bars and adjust to 2 angles. Below in Figure 3.5., the model of the mounting system designed in Creo, and the 3D printed version are shown. Figure 3.6. then shows the 3D printer used to create the mounting system.

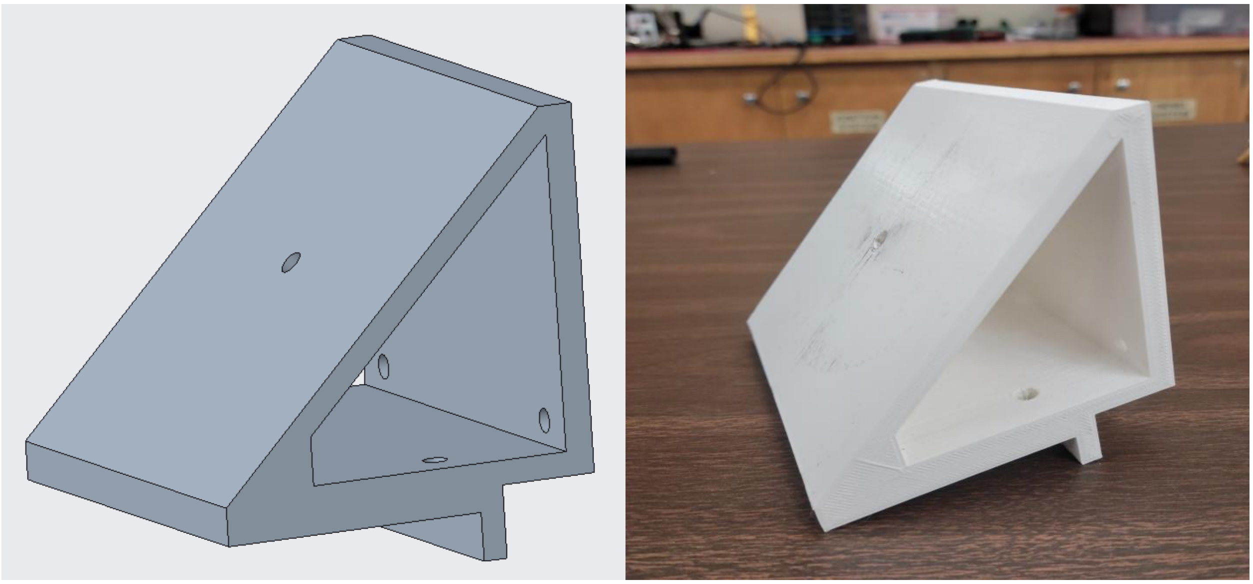


Figure 3.5. Model of sensor mounting system designed in Creo Parametric 4.0 and 3D printed output.

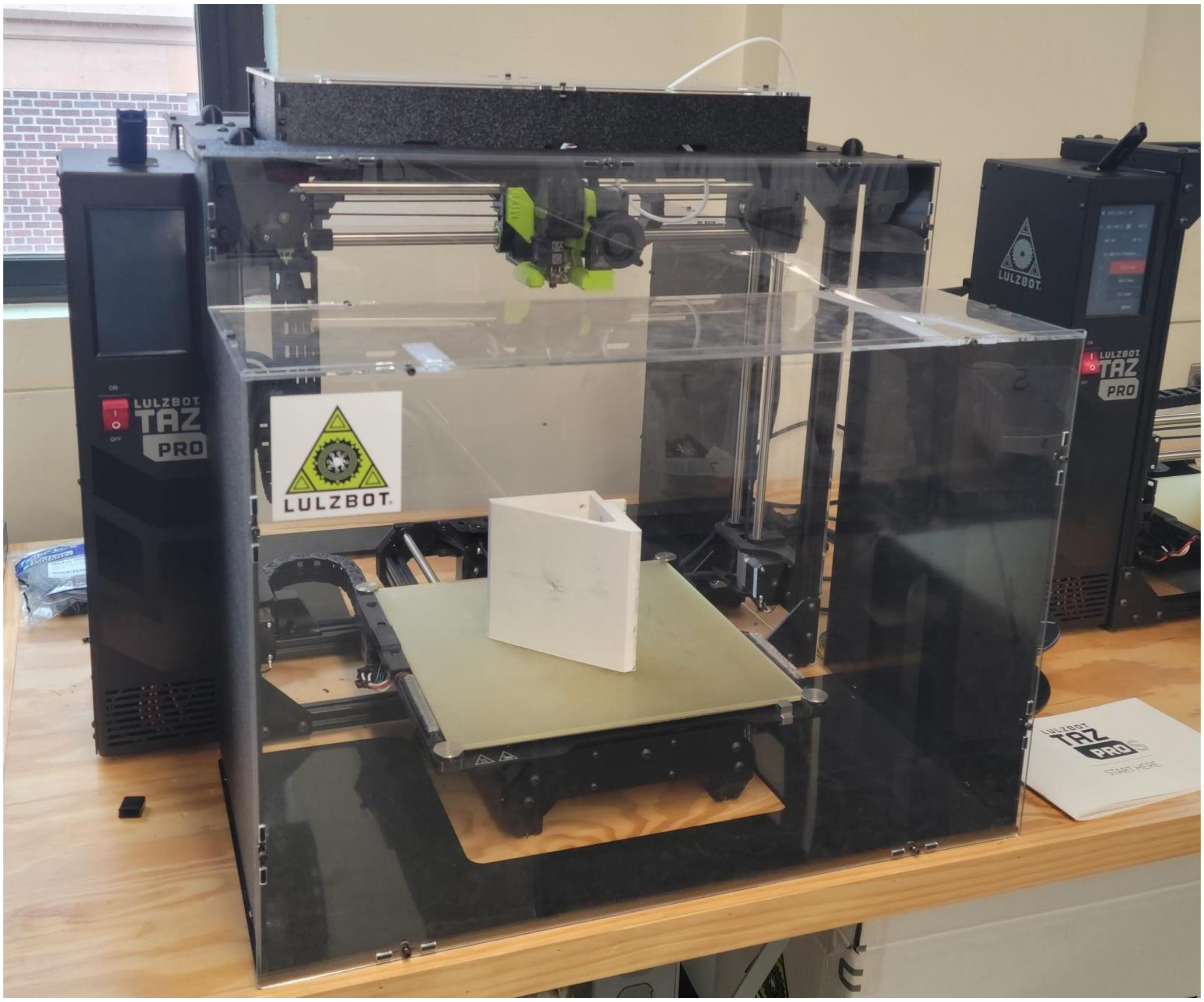


Figure 3.6. Lulzbot Taz Pro 3D printer used to create sensor mounting system.

This model was then 3D printed using PLA in a Lulzbot 3d printer. By using a higher fill level, the component was studier than in previous trials. There were many designs attempted but this design was able to be attached to either bar easily and the angle was altered to 30° or 45°. Figure 3.7. shows the LiDAR sensor mounted on the bottom bar of the Mini Weedbot.

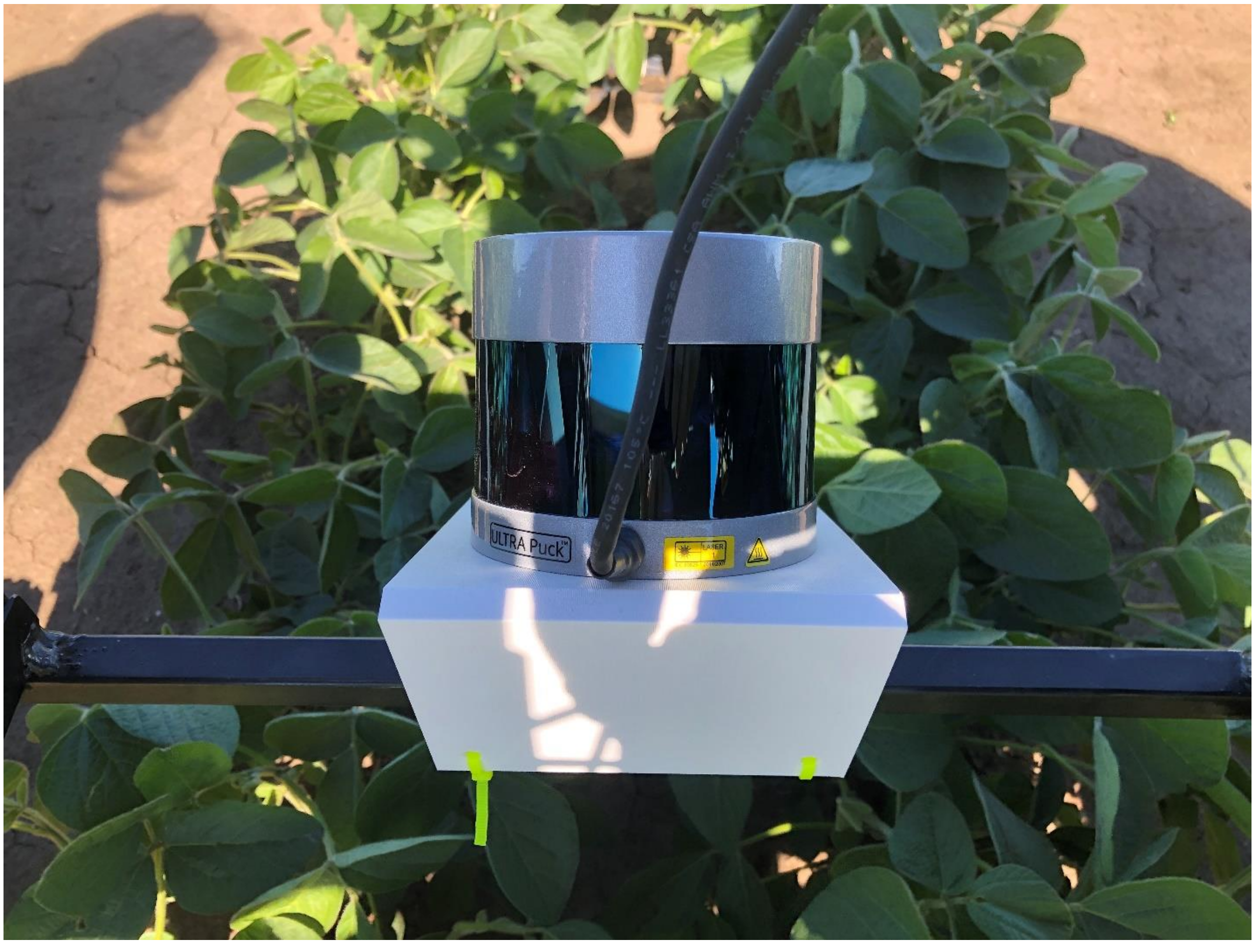


Figure 3.7. LiDAR sensor mounted on Mini Weedbot.

3.3. Precision Agriculture Robot

The precision agriculture team working with Dr. Xin Sun has created multiple robots that can be used for field testing. In this study, the robot used was the “Mini Weedbot” built by Dr. Sun’s precision agriculture group at NDSU. The Mini Weedbot is controlled by a remote control, with four 12 Volt batteries to power the robot. Two of these batteries run the motors that are directly linked to the wheels to drive and steer the robot. The other two batteries are used for the control system for the sensors connected to the robot. The figure below shows the frame utilized for this robot created in Creo Parametric 4.0.

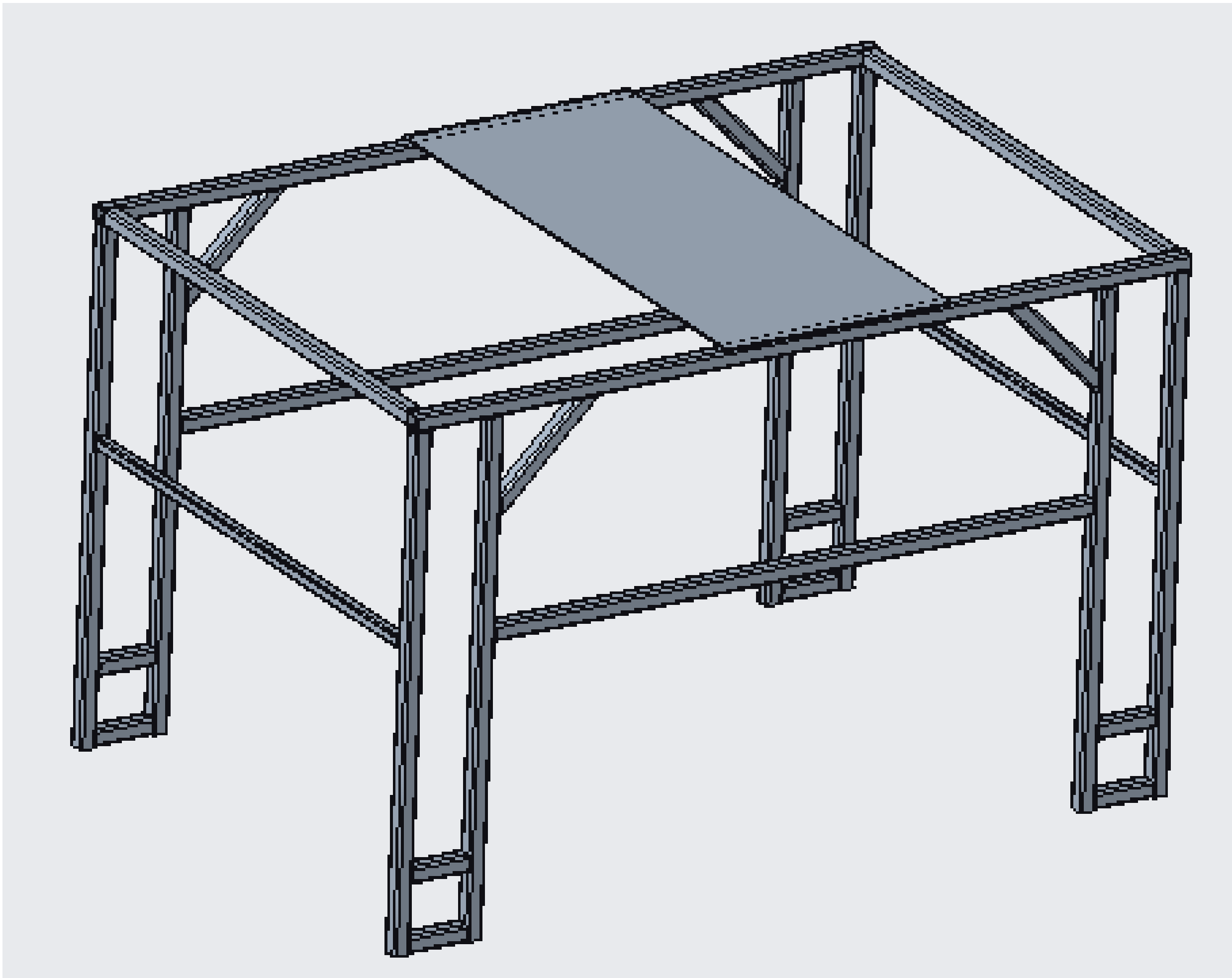


Figure 3.8. Mini Weedbot frame designed in Creo Parametric.

Attached to the frame is a raspberry pi, which is used as the central controller and connects the sensors attached to the robot back to a laptop. The robot was equipped with GPS, RTK (real-time kinetics), and the LiDAR sensor for this experiment. The data set being used came solely from the LiDAR sensor as the robot was manually driven down the rows for this experiment. The GPS and RTK were connected for the robots' autonomous functions. Figure 3.9. shows the Mini Weedbot as it was set up for these trials. The LiDAR sensor is attached to the front of the robot as shown by the arrow.

Figure 3.9. Mini Weedbot using a Velodyne VLP-32C LiDAR sensor attached to the front. Built by Dr. Xin Sun’s PAG team.

The raspberry pi is connected to the laptop which saves the data. This process allows for the software, Veloview – which is provided by Velodyne for free and is compatible with the sensor used – to record directly from the LiDAR sensor. This experiment was conducted by manually driving the robot and manually starting and stopping the recording process on Veloview. This process can eventually be run autonomously for future trials and compared to the results from this data. Figure 3.10. below shows some key features of the Mini Weedbot.

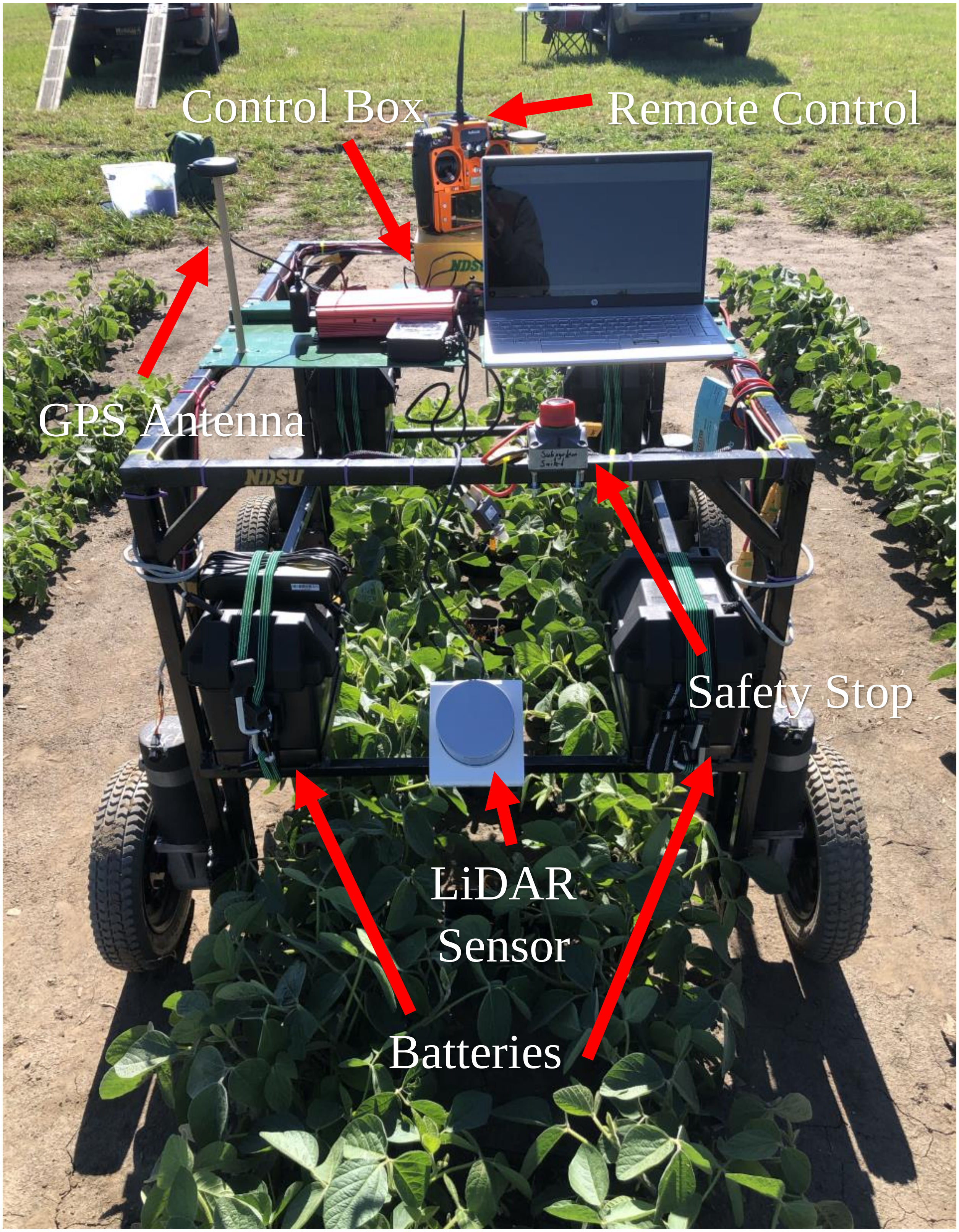


Figure 3.10. Annotated image showing aspects of the Mini Weedbot.

The robot is powered by 4 12-volt batteries. These are mounted above each of the wheels. The batters run both the motors for the wheels as well as power the sensors and controls on the Mini Weedbot. The Mini Weedbot can be driven using the remote controller seen in Figure 3.10. or autonomously using GPS or RTK input. For this experiment, the manual remote control was used to operate the machine.

3.4. Experimental Method

Through experimental trials, the relationship between the return intensity of each laser pulse and the distance that the laser travels to the object is explored. By running multiple trials at 2 different heights and 2 different angles, the relationship can be better understood. Using a UGV, trials were conducted to test the relationship in an agricultural setting. Each trial was conducted by mounting the LiDAR sensor to the front of the Mini Weedbot at a specific height and angle. This was then run from one end of the field, directly over the row of crops with the LiDAR sensor centered on the robot. Three conditions were set, each with a set angle for the LiDAR sensor to be mounted from the ground and at a specified height. Each condition is shown in Figures 3.11. (a), (b), and (c).

(a)

Figure 3.11. References for the angle and height of (a) Condition 1, (b) Condition 2, and (c) Condition 3 using Autocad.

(b)

Figure 3.11. References for the angle and height of (a) Condition 1, (b) Condition 2, and (c) Condition 3 using Autocad (continued).

(c)

Figure 3.11. References for the angle and height of (a) Condition 1, (b) Condition 2, and (c) Condition 3 using Autocad (continued).

Each condition's measurements are listed in the table below. The trials were conducted at both 30° from the horizontal axis, which was what the ground was considered, and 45° from the horizontal axis. The lower bar mount elevated the sensor 20 inches from the ground, while the higher bar was 37 inches above the ground.

Table 3.1. The angles and heights used for each experiment's conditions.

Conditions	Angle (Degrees)	Height (Inches)
Condition 1	30	20
Condition 2	45	20
Condition 3	45	37

Each variation of the height or angle allowed for a better understanding of the relationship between the 2 variables being compared. Expanding upon that, the changes in height or angle can be compared to determine if one had a more statistically significant impact. Doing 3 trials with each of the setups listed above allows for more accurate data collection with the repeated tasks. This along with the consistency of the environmental setting were both intended to keep variables, other than the ones being focused on in the statistical analysis, from interfering with the data collected.

3.5. Statistical Analysis Method

Using descriptive statistics on the data sets acquired from these trials, the statistical significance of the relationship between these 2 variables – the return intensity and the distance – can be determined. One statistical analysis method considered for this data set was linear regression analysis. As summarized in "The Assumptions of the Linear Regression Model" by Poole and O'Farrell, linear regression modeling requires making assumptions depending on what the model is trying to attain. If these assumptions are unable to be satisfied, alternative techniques may be used to determine the importance of the variation. It is important to note that these assumptions exist and need to be considered before a model can be valid. For this model, the following assumptions were made with X and Y being the variables of distance and the return intensity of the laser.

1. The relationship between X and Y is linear.
2. Any value of X has the same variance of residual, this is referred to as homoscedasticity.
3. X and Y are independent of each other.
4. X and Y values are normally distributed.

How these affect the output is another important consideration. Normality assumptions for large populations may be unnecessary as it does not always provide valid results. Additionally, transformations in the data may lead to bias in the full model (Schmidt and Finan). However, with such a large data set being analyzed the normality assumption is a relevant concern. The nonparametric analysis is a method that can be considered without utilizing the normality assumptions.

Along with the assumptions noted before, outliers are another factor to consider in statistical analysis. How to detect outliers and ways to understand their significance in the model are important considerations. Zwilling wrote about outliers in the dissertation, “New Approaches for Outlier Detection”. This dissertation provided an overall explanation of outliers. It also illustrates some methods to find outliers such as Multivariate Voronoi Outlier Detection (MVOD). Another method to factor how statistically significant is Cook’s Distance. Dr. Marzjarani shows the practical application of this in “Sample Size and Outliers, Leverage, and Influential Points, and Cooks Distance Formula”. By using Cook’s Distance, one can check if the outliers in a data set are statistically significant. If they are, they must be explained or dealt with in some manner.

However, if they aren't, they can be disregarded as they don't significantly impact the output of the model. Using Cook's Distance on a sample of this data was tested to determine whether the outliers in this model would impact the results.

Cook's Distance: $$Di = \frac{\sum_{j=1}^{n}\left(Y_j - Y_{j(i)}\right)^2}{(p+1)\sigma^2} \quad \text{(Eq. 1)}$$

When applied, the data showed that the outliers held no statistical significance to the data set. Due to this, they can be omitted without a significant impact on the final output. Below shows the graph of Cook's Distance in which the points fall within the acceptable range to omit the outlying data.

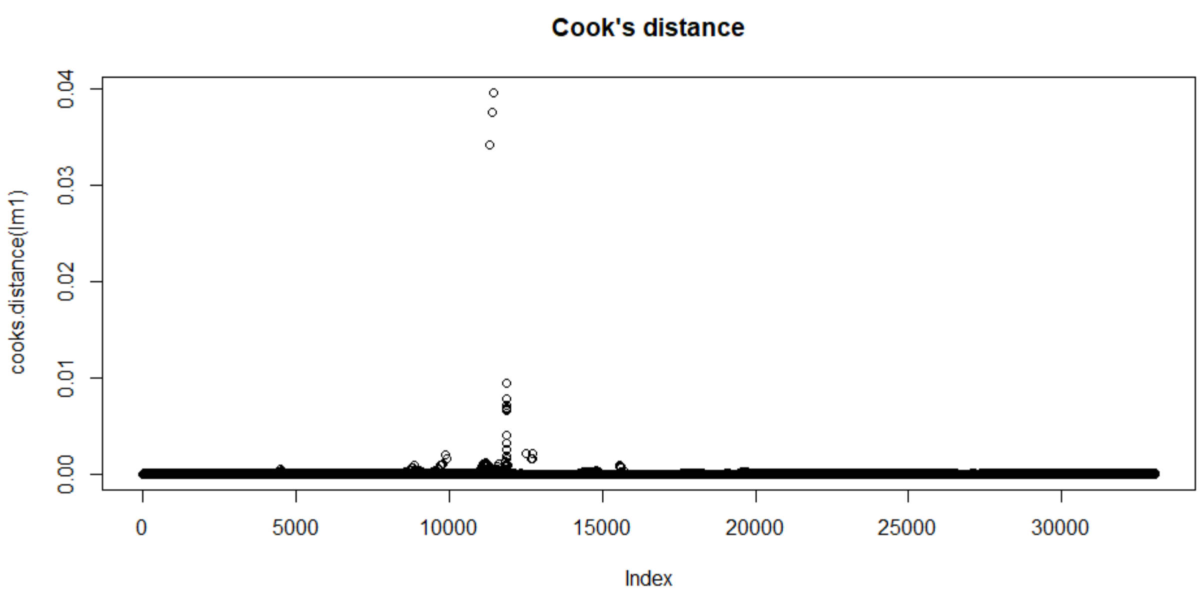


Figure 3.12. Cook's Distance tested on sample data set to determine statistical significance on outliers.

Due to the determination that the outliers have no statistically significant effect on the results of the data and the sheer amount of data that these trials acquired, the outliers were omitted. This allowed for a much cleaner statistical model and aided in determining what relationship is seen between the return intensity and the distance between the sensor and the object.

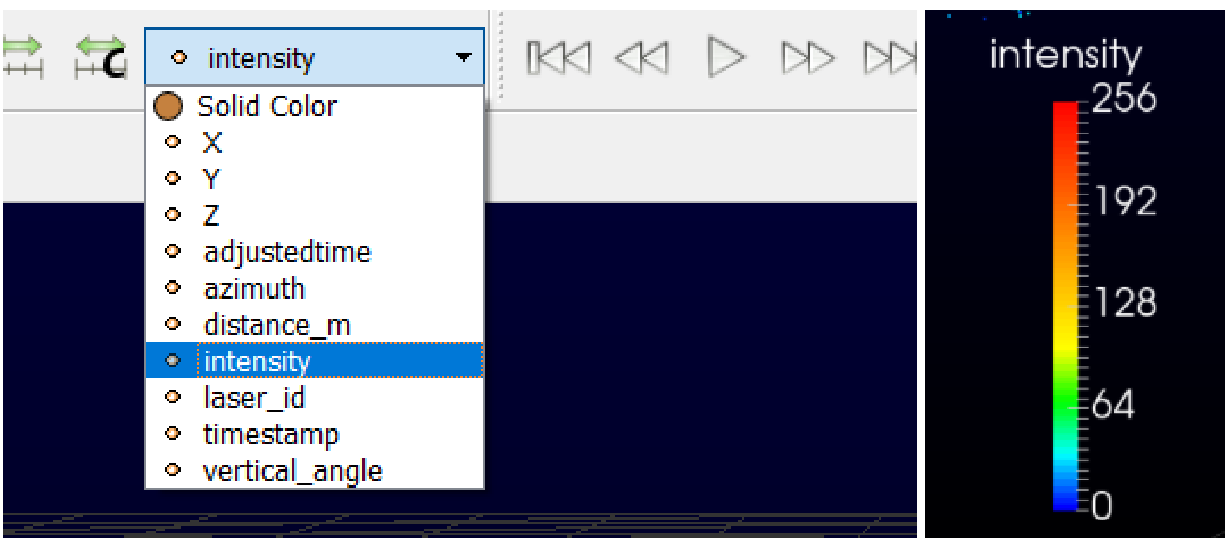
4. RESULTS AND DISCUSSION

4.1. LiDAR Sensor Output

Each trial was recorded using Veloview, a free software provided by Velodyne that is compatible with Velodyne LiDAR sensors. The output of the data in Veloview is uploaded to a point cloud that can be watched frame by frame in the software. The data can also be downloaded into a .csv file. The outputs of this study will be discussed in this chapter.

4.1.1. LiDAR Image Acquisition

In Veloview, the point cloud for multiple variables is available. For each variable, the point cloud color scale is adjusted based on the data output. Both the variables possible and an example of the intensity scale are seen in Figure 4.1.



(a) (b)

Figure 4.1. (a) Point cloud variable options (b) Intensity color scale.

The point cloud for this data shows the intensity of the return beams for each point it returned from. The image in Figure 4.1. below shows the point cloud recorded during trial 1 for Condition 1 from frame 1556.

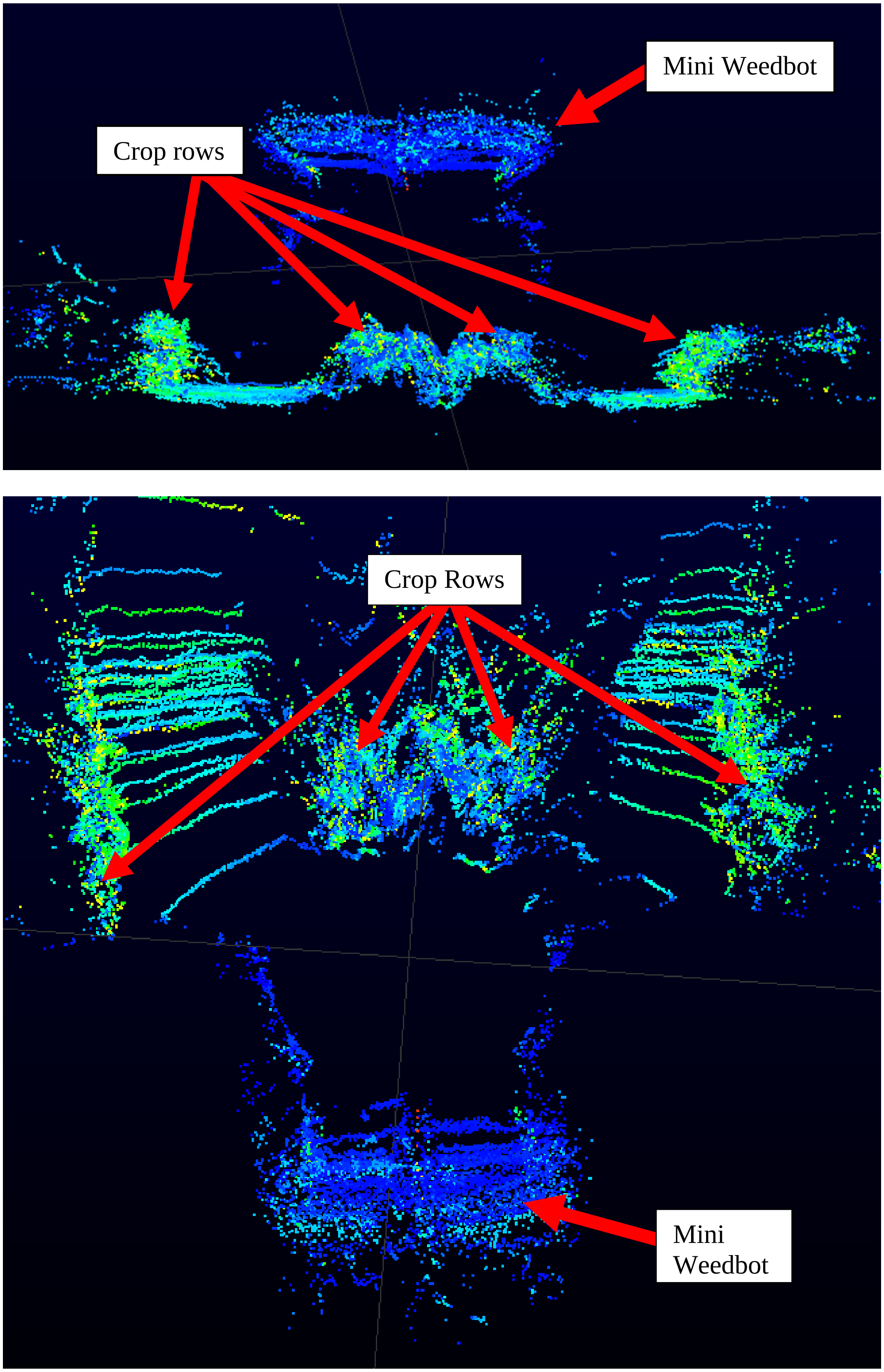
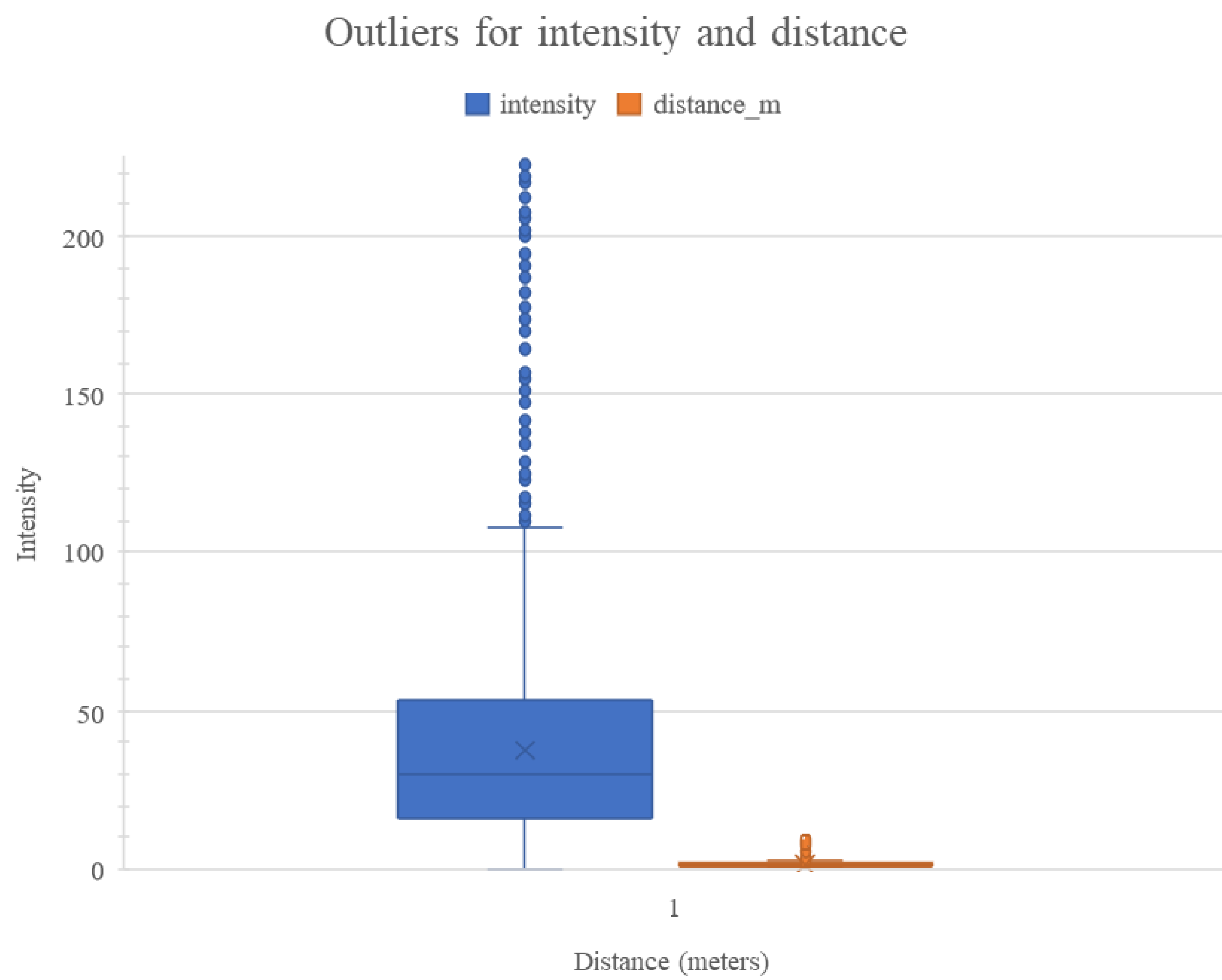


Figure 4.2. Veloview software output for LiDAR sensor.

As illustrated in Figure 4.1. (b), the color scale for intensity has red being the highest intensity possible at 256. Low intensity returns closer to 0 are seen as blue. As seen in Figure 4.2., the mainly blue section is the robot that the sensor was mounted to as it was behind the LiDAR sensor. As there is a 360° view for this LiDAR sensor, it is visible however, it does not have a strong intensity return. The return intensities for data using field crops while not listed in Table 2.1, which was discussed earlier, should fall between coniferous trees (Typ. 30) and deciduous trees (Typ. 60) as those are similar biological materials. The crop rows referred to in Figure 4.2., are a mix of greens and blues, showing that the intensity return is anywhere from 0 to around 64 which fits with the maximum intensity return but not the lower intensity return. There is a large amount of variation in intensity returns when looking at the raw, unfiltered data. This is logical when using field testing for experimental data. However, filtering the data by looking only in front of the robot at the crops helps determine the relationship between the return intensity from the crop rows and the distance.

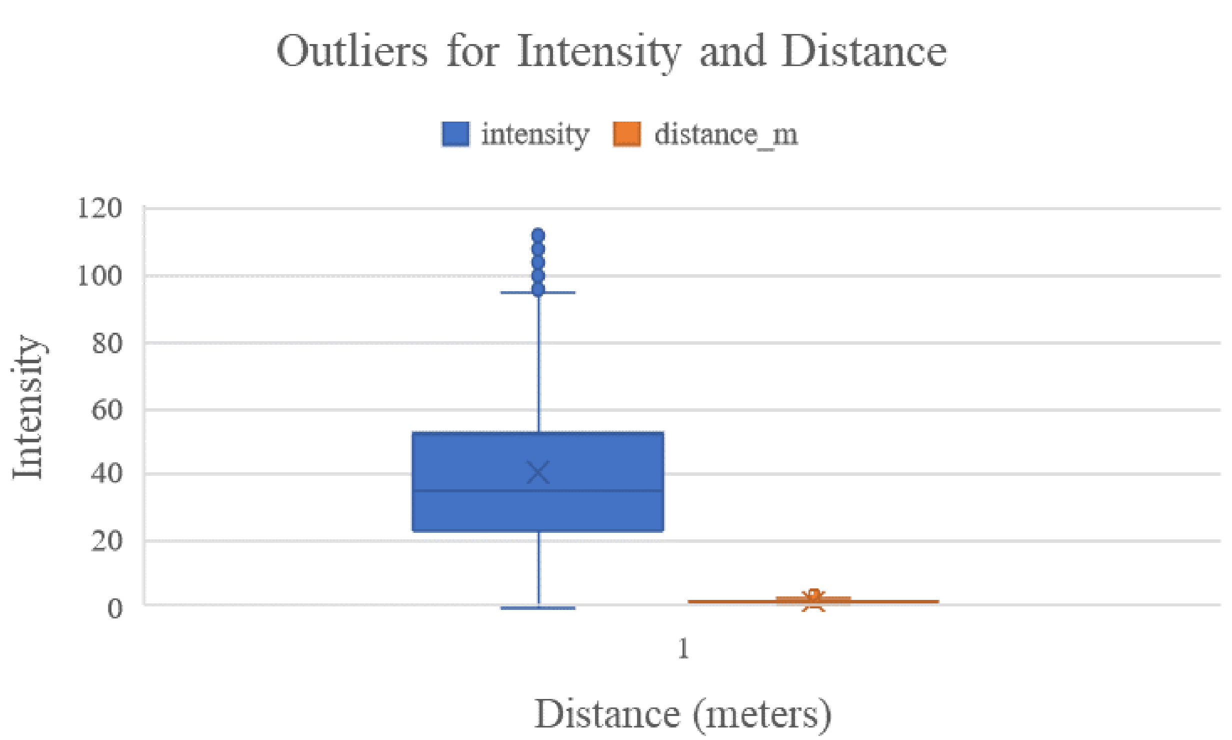
4.1.2. LiDAR Numerical Data Acquisition

After recording each trial, the data was downloaded from Veloview into a .csv file for each frame of data. The appendix shows 100 lines of the excel data output from frame 1556 of Condition 1 – trial 1. The individual frames of data for each trial contained around 33,000 lines of data in excel. By filtering out the outliers in the data sets, the trials were much smaller but still had a large amount of data. Using a simple command prompt, the filtered trials were merged into a larger file for each trial. Each trial still had outliers present after the data was filtered. Figure 4.3. shows the box plot used to identify the outliers for trials from Condition 1(a) and Condition 3(b).



(a)

Figure 4.3. Box and Whisker plot showing the outliers for (a) Condition 1 – trial 2 and (b) Condition 3 – trial 1.



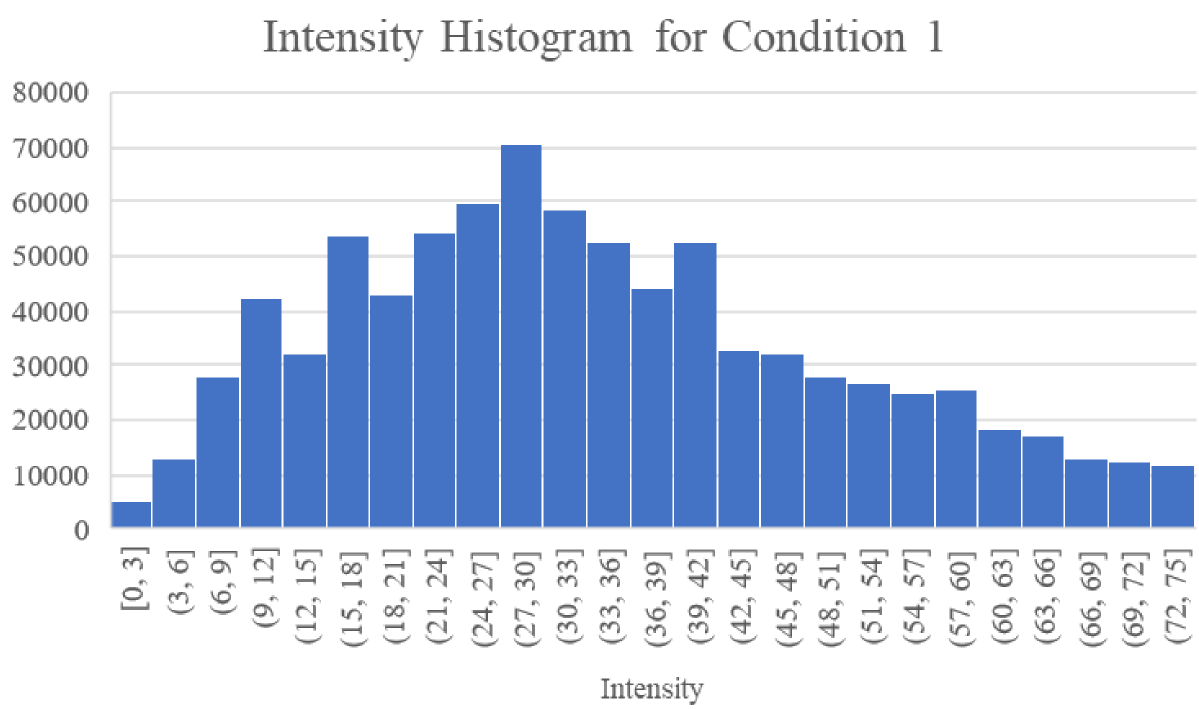
(b)

Figure 4.3 Box and Whisker plot showing the outliers for (a) Condition 1 – trial 2 and (b) Condition 3 – trial 1 (continued).

Eliminating the outlying data points allowed for cleaner results for each condition. Conditions 1, 2, and 3 had 851028, 957937, and 712773 data points respectively after the removal of any outlying points. Descriptive statistics were used to analyze the data overall. Normality tests in excel were then used to determine if the data would fit the assumptions required for simple linear regression and ANOVA tests. Non-parametric tests and logistic regression will also be conducted to determine if there is any relationship between the return intensity of the laser emitted from the LiDAR sensor and the distance the laser traveled from the sensor to the object.

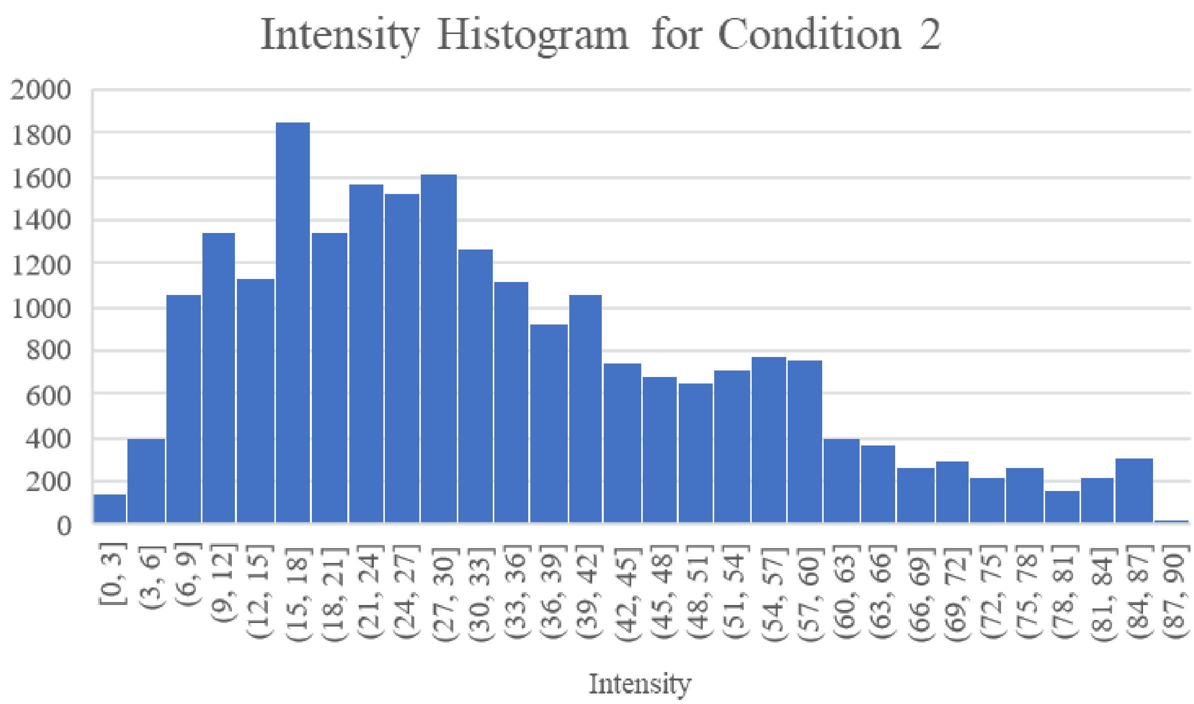
4.2. Normality Tests

Normality in the data is important to consider when looking to use tests like simple linear regression. These tests assume that the data is normally distributed as it gives the most accurate results. Due to that, the first tests conducted were to test the distribution of the data. Histograms of the data demonstrate the distribution of the data in an easily visualized way. The plots in Figure 4.4. and Figure 4.5. show the histograms for the intensity and distance data collected.

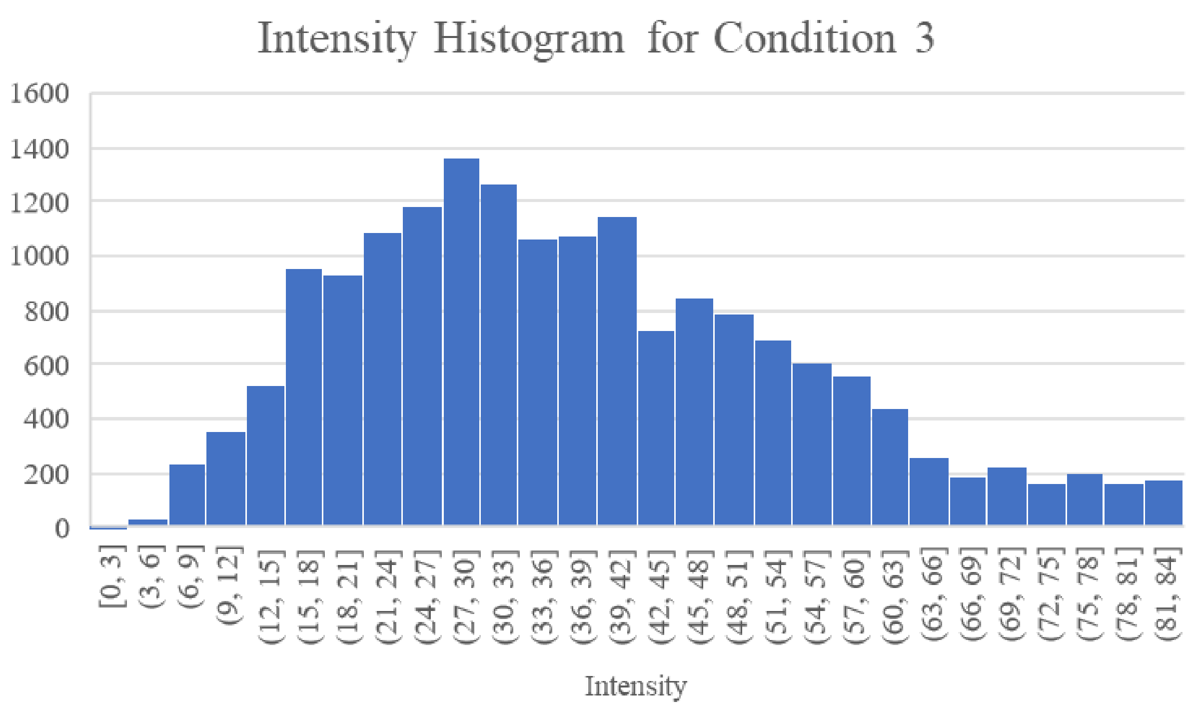


(a)

Figure 4.4. Histogram showing the distribution of intensity values for (a) Condition 1, (b) Condition 2, and (c) Condition 3.

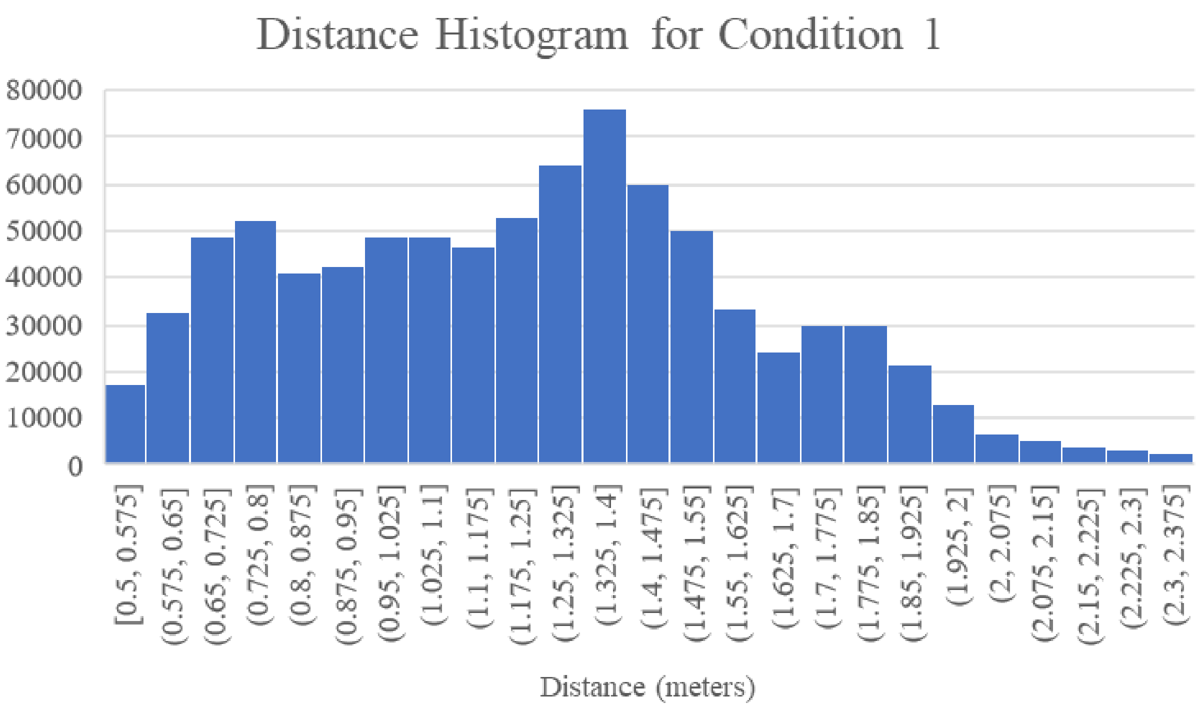


(b)

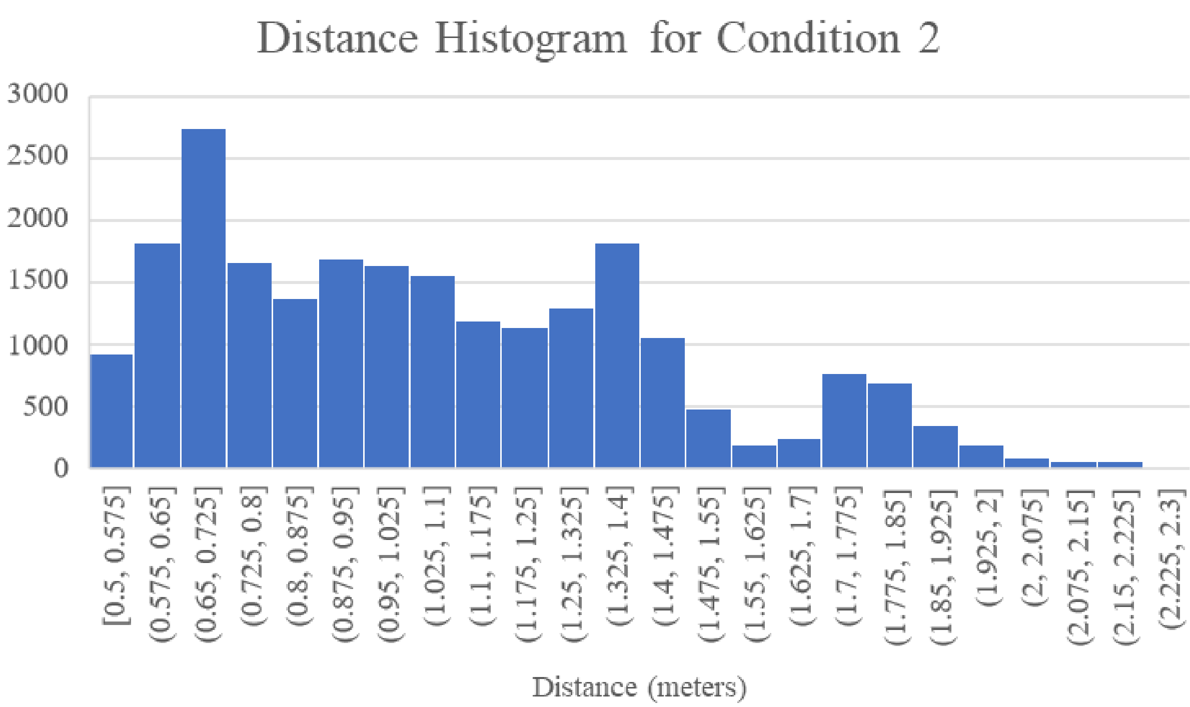


(c)

Figure 4.4. Histogram showing the distribution of intensity values for (a) Condition 1, (b) Condition 2, and (c) Condition 3 (continued).

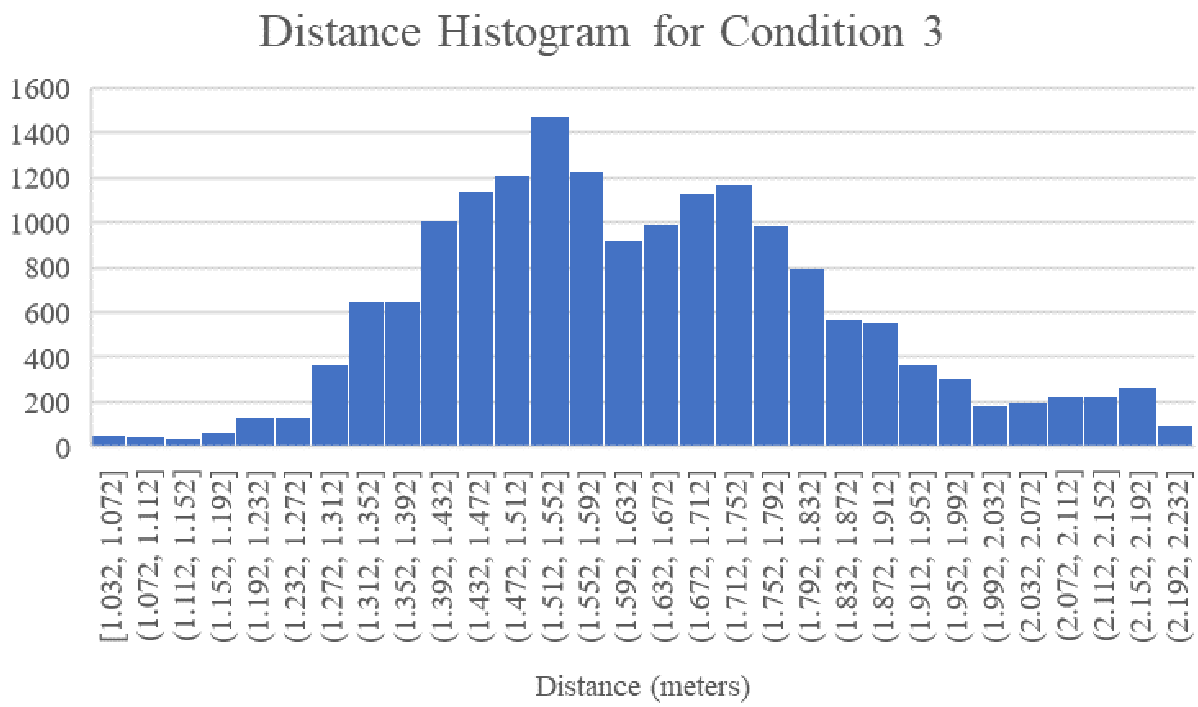


(a)



(b)

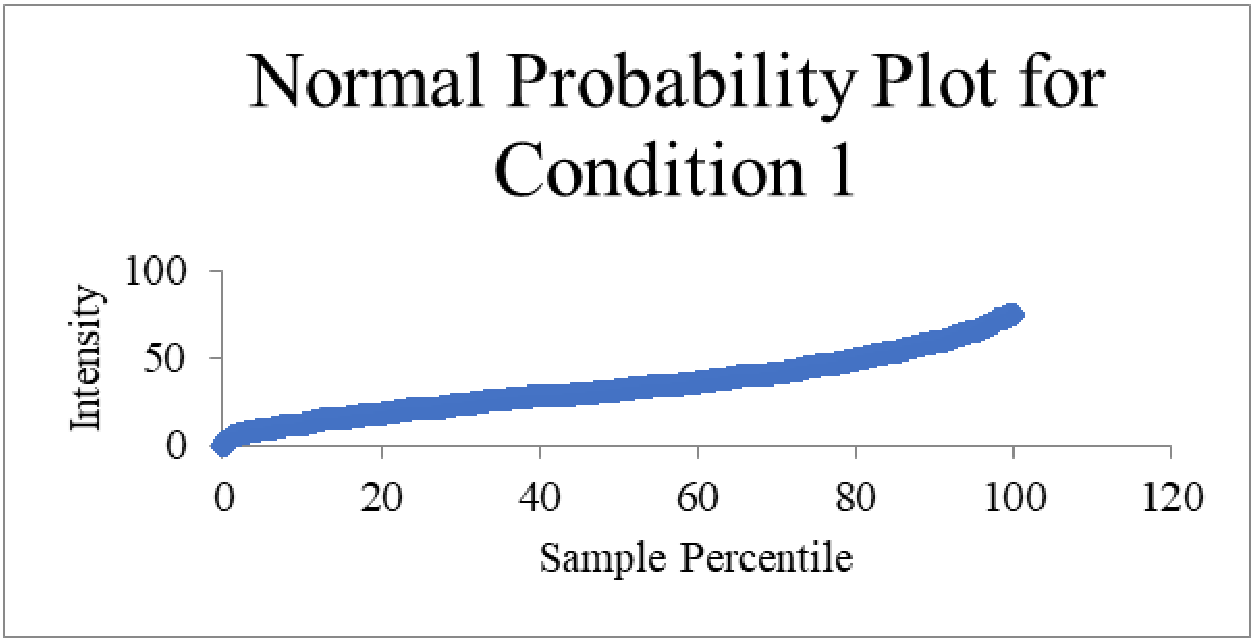
Figure 4.5. Histogram showing the distribution of distance values for (a) Condition 1, (b) Condition 2, and (c) Condition 3.



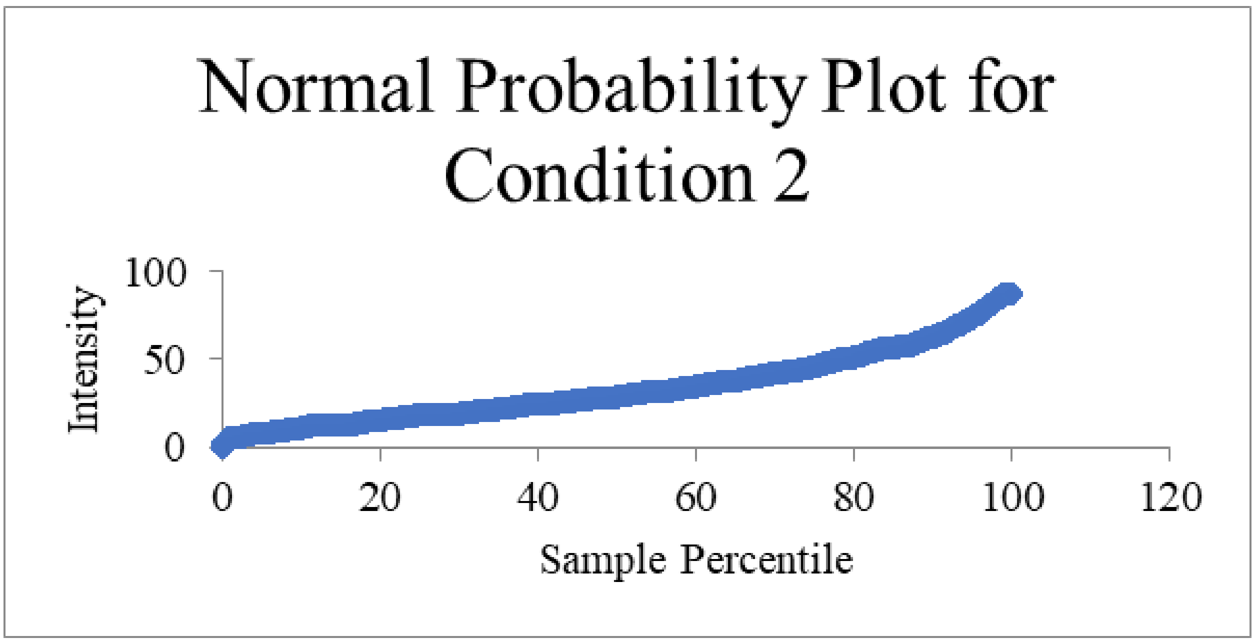
(c)

Figure 4.5. Histogram showing the distribution of distance values for (a) Condition 1, (b) Condition 2, and (c) Condition 3 (continued).

As the histograms for each condition show, the data is skewed to the left for both the return intensity values and the distance values. This means more of the data falls in the lower intensity values and smaller distance values which is consistent through each trial. Being skewed to the left also indicates that the data collected is not normally collected. Normal probability plots are another way to check if there are other concerns in the data. These plots are a tool to help identify outliers, skewed data, and other significant departures from what is considered normal. This is a useful tool for determining any issues in the data before or during in-depth analysis. The graphs below show the normal probability plots for each condition in this study.

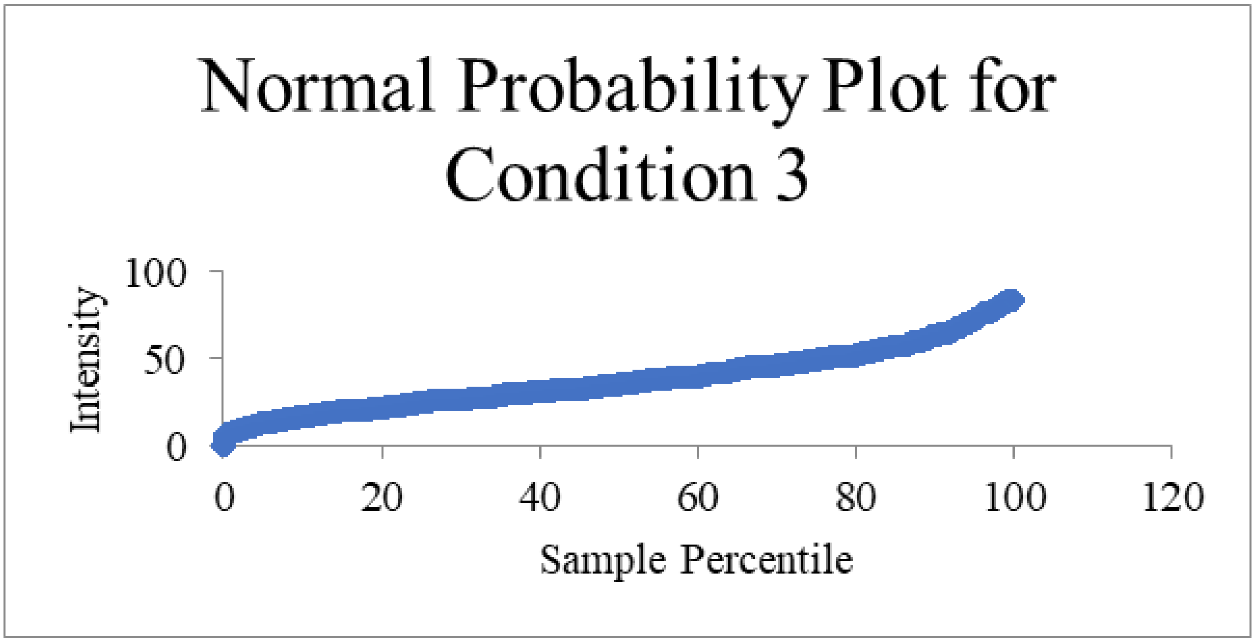


(a)



(b)

Figure 4.6. Normal probability plot of intensity for (a) Condition 1, (b) Condition 2, and (c) Condition 3.



(c)

Figure 4.6. Normal probability plot of intensity for (a) Condition 1, (b) Condition 2, and (c) Condition 3 (continued).

The normal probability plots for each condition are very similar. They each follow a mostly linear trend with slight a slight curve up near the end. A clear linear trend is what would be considered a good normal probability graph, therefore this also does not support the assumption that the data is normal. Another way to check the normality is to conduct tests on the data set using methods such as the D'Agostino-Pearson normality test. The results of that test for each condition are shown in Table 4.1. below.

Table 4.1. D'Agostino-Pearson test results for Conditions 1-3.

	Condition 1		Condition 2		Condition 3	
	Intensity	Distance	Intensity	Distance	Intensity	Distance
DA-stat	43504.4	31288.1	75672	66618.6	33134.1	45194.6
p-value	0	0	0	0	0	0
alpha	0.05	0.05	0.05	0.05	0.05	0.05
normal	no	no	no	no	no	no

As shown in Table 4.1., the data did not pass the normality test. Not passing the normality tests does not mean simple linear regression or ANOVA tests may not be attempted but the results will most likely not be conclusive. Non-parametric tests and logistic regression are what will be more likely to determine significant results since the data is not normally distributed. The results of a range of tests conducted on this data set will follow in this chapter.

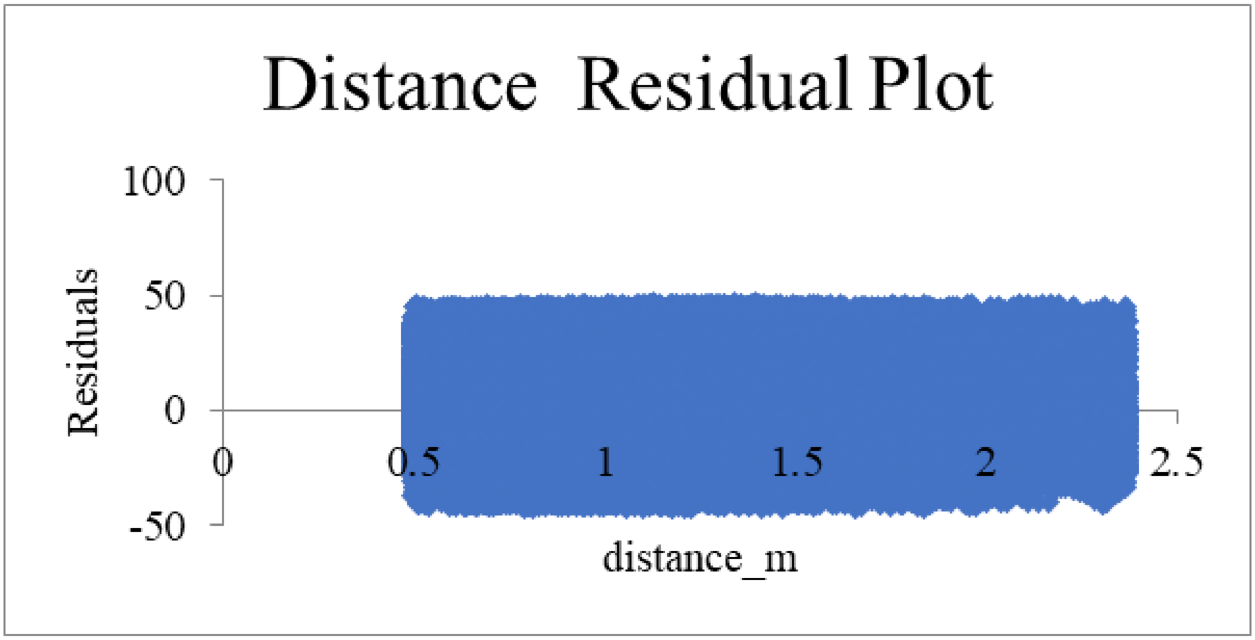
4.3. Linear Regression Analysis

The regression analysis between the x variable, the distance from the object to the sensor in meters, and the y variable, the intensity of the return pulse, results are shown in this section. Comparing these 2 variables, the statistical significance of the impact of the distance on the intensity can be illustrated and compared for each condition. Each trial produced similar results that are shown in the tables and figures that follow. The null hypothesis or H_0 for this study is the $\beta = 0$ where β refers to the intensity output. The alternative hypothesis or H_a is that $\beta \neq 0$. Using this model, the best fit can be determined. The R-squared values are an indicator of the best fit for the model.

Table 4.2. Best fit variables for each condition.

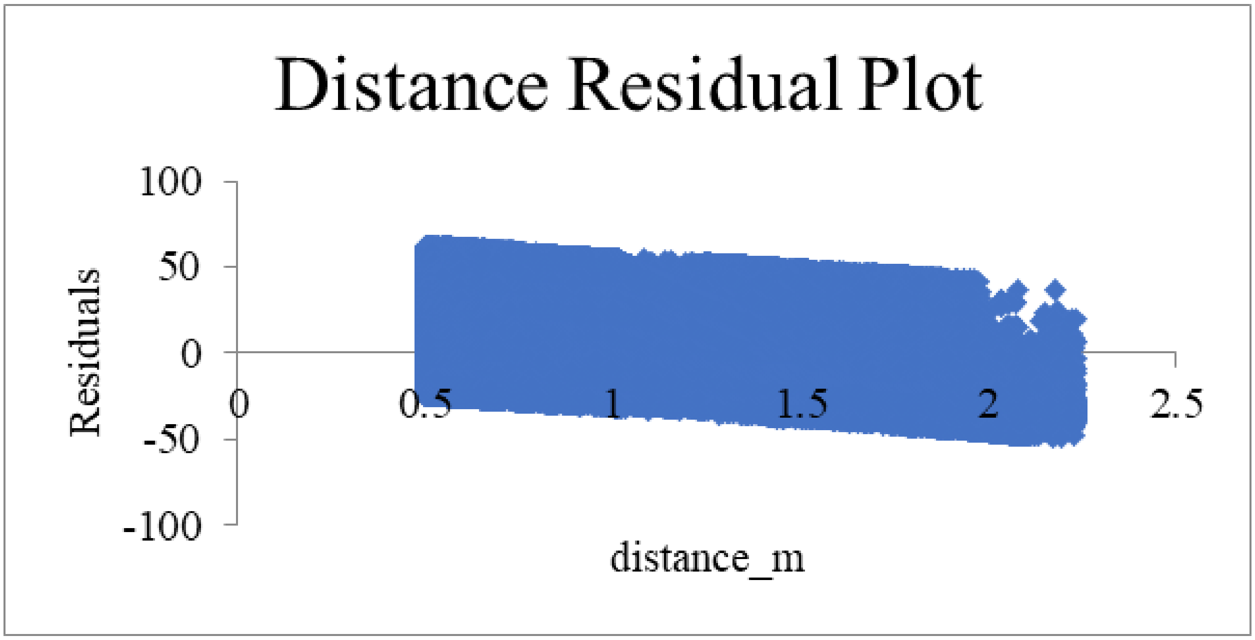
	Condition 1	Condition 2	Condition 3
Multiple R	0.18086832	0.26054874	0.21678643
R Square	0.03271335	0.06788565	0.04699636
Adjusted R Square	0.03271221	0.06788468	0.04699502
P-value	0	0	0

For each condition, the R-squared values were very low. These values indicate there is almost no relationship between the 2 variables. However, when looking at the p-values for these data sets, the value of each condition was below 0.05. This concludes that the results found were statistically significant. A low p-value also indicates that the null hypothesis should be rejected and therefore the alternative hypothesis of $\beta \neq 0$ is true. However, the residual plots also indicate that the model is not a good fit. Figure 4.7. shows the residual plots for each condition. The residuals are a measure of how far, vertically, a point is from the regression line. It tells the difference between the actual value and the predicted value.

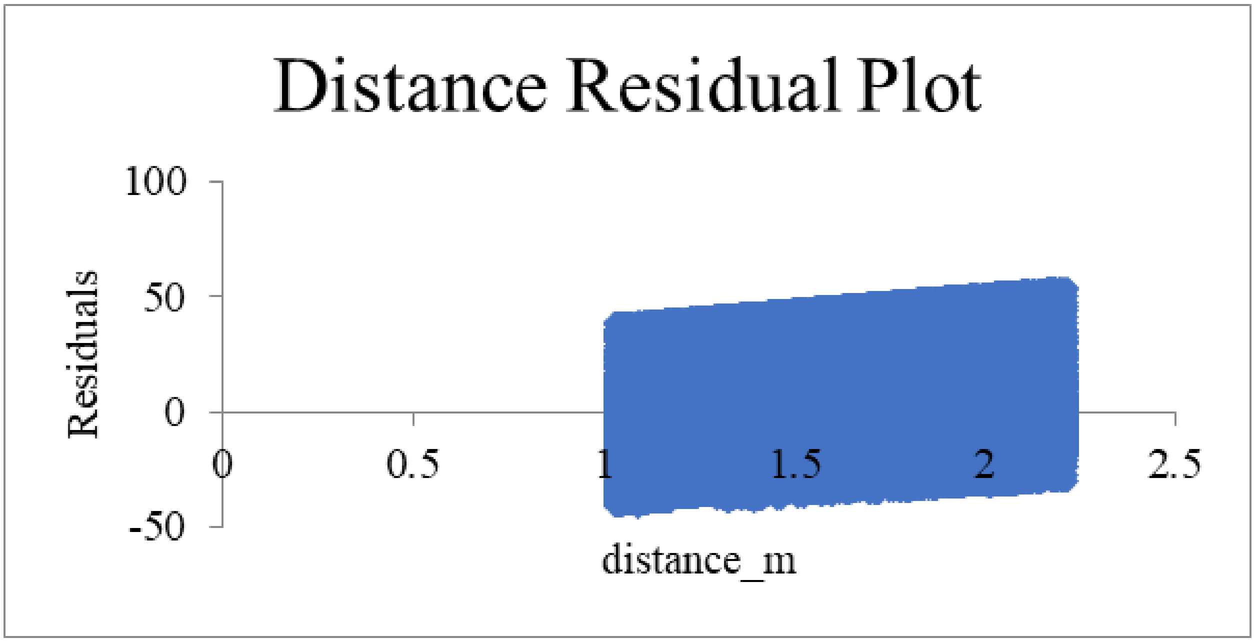


(a)

Figure 4.7. Residual plots for (a) Condition 1, (b) Condition 2, and (c) Condition 3.



(b)



(c)

Figure 4.7. Residual plots for (a) Condition 1, (b) Condition 2, and (c) Condition 3 (continued).

The residual plots for each condition are all varied but the result is the same. All trial residuals fall between the range of -100 to 100 but all follow some sort of pattern. It is important to note that an ideal correlation would show a residual plot with random scattering on both sides of the identity line, which is zero on these plots. These plots do not show that ideal image, as they all have some sort of trend. The residual plots and the R-squared values both tell us that the linear regression model is not a good fit.

4.4. Single Factor ANOVA Test

A single-factor ANOVA test is another way to analyze the data collected in these trials. ANOVA tests can determine the variability in the data affects the repeatability of this data. Table 4.3. shows the ANOVA output from a trial for each condition using these hypotheses.

Table 4.3 ANOVA table for (a) Condition 1, (b) Condition 2, and (c) Condition 3.

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	4.57E+08	1	4.57E+08	3198468	0	3.841464
Within Groups	2.43E+08	1702052	142.921			
Total	7E+08	1702053				

(a)

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	5.01E+08	1	5.01E+08	2450210	0	3.841464
Within Groups	3.92E+08	1915870	204.4258			
Total	8.93E+08	1915871				

(b)

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	4.71E+08	1	4.71E+08	3066856	0	3.841465
Within Groups	2.19E+08	1425542	153.568			
Total	6.9E+08	1425543				

(c)

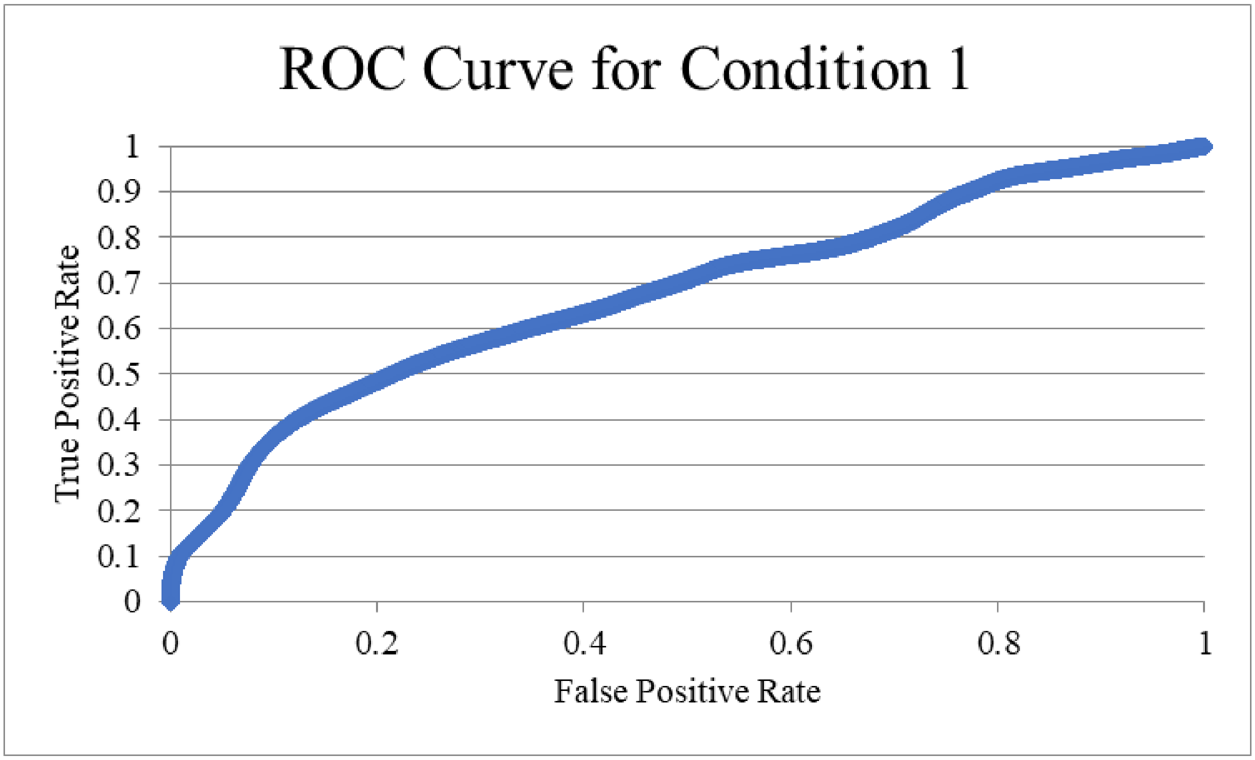
With the single factor analysis, the consistency between the trials is shown by the F value and the F critical value. The F critical values are the same and the F values fall within a reasonable range. This means the variation in the trials was consistent through each Condition. This is a good indicator that the data collected is repeatable.

4.5. Logistic Regression Analysis

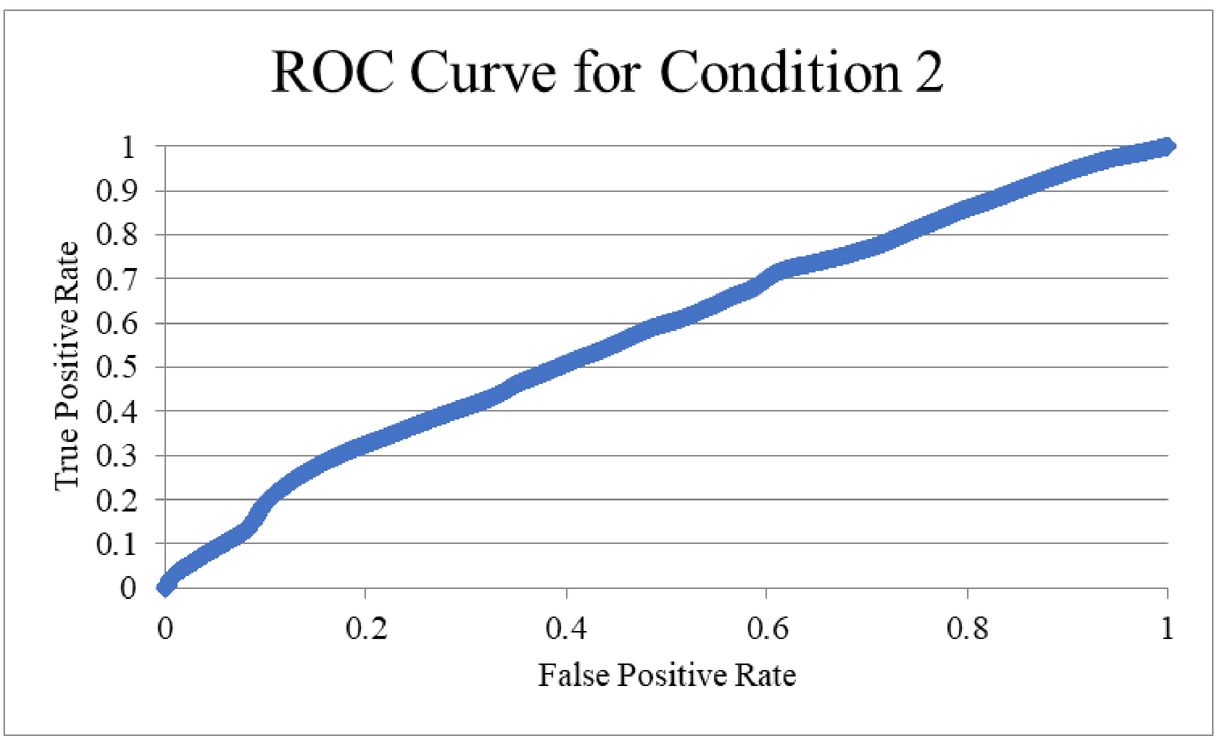
Logistic regression analysis using the return intensity of the laser beam, the distance the beam traveled, and whether the vertical angle was positive or negative was used to create the model output below. The model is created with the logistic regression equation.

Logistic Regression: $$y = Log\left(\frac{p}{1-p}\right) \qquad \text{(Eq. 2)}$$

In the logistic regression equation, p is the probability of success. A good way to visualize this model is a ROC curve or receiver operating characteristic curve which is shown below in Figure 4.8. for each condition.

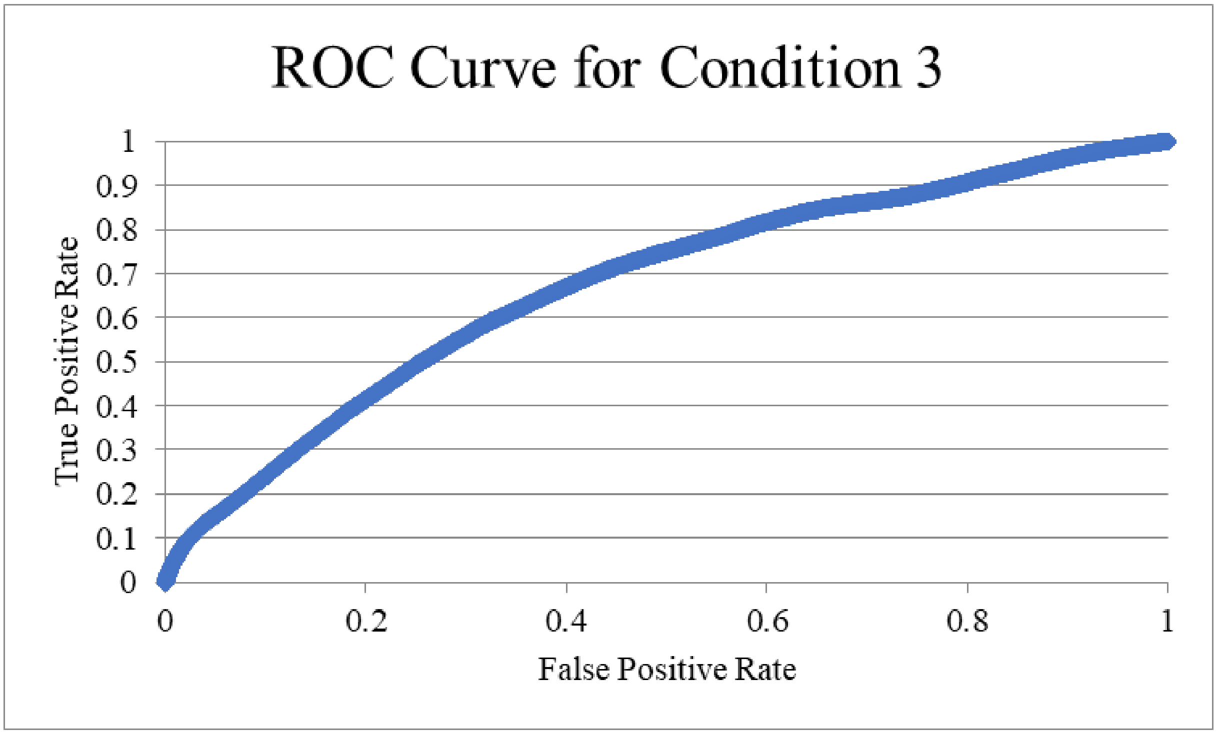


(a)



(b)

Figure 4.8. ROC Curves for (a) Condition 1, (b) Condition 2, and (c) Condition 3.



(c)

Figure 4.8. ROC Curves for (a) Condition 1, (b) Condition 2, and (c) Condition 3 (continued).

A ROC Curve is an indicator used in logistic regression to determine if the classifier is good for the model or random. Better performance classifiers are closer to the top left corner of the graph. The graphs for Conditions 1 through 3 are much closer to a diagonal line across the graph which indicates they are much closer to a random classifier. Another way to analyze if this model fits the data is by looking at the R squared values. There are multiple tests to determine the R squared value for logistic regression. For this model, the Cox-Snell method and the Nagelkerke method were looked at. The table below shows the R squared values and p-values.

Table 4.4. R squared values and p-values for Conditions 1, 2 and 3.

	Condition 1	Condition 2	Condition 3
p-value	0	0	0
R-sq (CS)	0.0866594	0.01885026	0.075637
R-sq (N)	0.1215755	0.02608286	0.1062079

The values for both methods of finding R squared indicate a low correlation between the variables. The p-values are less than 0.5 which means the variables are statistically significant. However, the combination of the R-squared values and the ROC curves determines that the logistic regression model does not fit the data well.

4.6. Chi-Square Test

The Chi-Square test is a non-parametric test that does not assume normality in the data. This test compares the observed results with the expected results to determine whether the difference between these results is due to chance or a relationship between the variables being tested. The variables being tested in this test are the return intensity of the laser beam and the distance the laser beam travels from the sensor to the object. The table below shows the results for each condition.

Table 4.5. Chi-Square Results for (a) Condition 1, (b) Condition 2, and (c) Condition 3.

CHI-SQUARE for Condition 1

	chi-sq	p-value	x-crit	sig	Cramer V
Pearson's	901441	0	35536.9	yes	0.11884
Max likelihood	622230	0	35536.9	yes	0.09874

(a)

CHI-SQUARE for Condition 2

	chi-sq	p-value	x-crit	sig	Cramer V
Pearson's	1160841	0	38559.2	yes	0.11735
Max likelihood	871406	0	38559.2	yes	0.10167

(b)

CHI-SQUARE for Condition 3

	chi-sq	p-value	x-crit	sig	Cramer V
Pearson's	544593	0	25231.9	yes	0.09537
Max likelihood	435873	0	25231.9	yes	0.08532

(c)

To determine the goodness of fit of the Chi-Square model, the chi-square value should be compared to the x-critical value. If the chi-square value is greater than the critical value, the model is significant which is shown in the fourth column. The p-values, which are less than 0.05, also indicate that the model is significant. The last column of information, Cramer's V, measures how strongly correlated the variables are on a scale from 0 to 1. In this case, the correlation between the return intensity and the distance the laser travels is very low on the scale. 0.1 is typically considered the minimum threshold for suggesting there is a relationship between the two variables. Condition 1 and Condition 2 average to over 0.1, meeting the minimum threshold. However, Condition 3 falls just under the threshold. What this indicates is that there is a correlation between the variables, particularly in Conditions 1 and 2, but that it is a very low correlation.

4.7. Discussion

The most conclusive results from the tests above come from the Chi-Squared test. The simple linear regression, single-factor ANOVA test, and logistic regression indicate no relationship between the two variables – the distance between the LiDAR sensor and the object and the return intensity of the laser pulses emitted by the sensor. The non-normality in the data affects the simple linear regression and ANOVA tests, and the logistic regression results prove that there is not a clear logarithmic trend in the data. The Chi-Squared test determined that there is a trend in the data. The large variation and large scope of the data could be affecting the results. However, the low p-value indicating statistically significant results and Cramer's V results are better indicators in my opinion of the statistical relationship between these two variables (Table 4.5). It is clear that there is not a linear or logarithmic trend in the data but that does not mean there is no correlation between the variables. This conclusion differs from studies by Tatoglu and

Pochiraju (2012), Bordin et al. (2013), and Hopkinson (2007) as they all focused on linear trends in their research.

Many studies both in agriculture and other research areas have covered similar topics. However, few have studied the relationship between the return intensity of a laser beam and the distance between the LiDAR sensor and the object. Each of the three previously mentioned studies compared laser intensity with distance in some way. Tatoglu and Pochiraju (2012) did a lab study on how the distance between the sensor and object affected the return intensity of the laser beam. What they found was a mostly linear relationship between distance and intensity. Their study differs from what was accomplished in this study as they tested over a much shorter distance, within 5 meters, and used samples in a lab rather than a field test as found in this paper. Bordin et al. (2013) and Hopkinson (2007) both did field studies. The field study conducted by Bordin focused on the intensity return of a laser scanner compared with distance. They found a direct relationship between the two variables. They were testing this in a forestry setting and were using the return intensity from a single tree which differs from the field testing conducted for this study. Hopkinson concluded the same thing as the previously mentioned studies, that there was a linear relationship between the intensity and peak pulse power concentrations where the surface encountered the emitted laser pulse which differs from both previous works as it is focused on how altitude affects the relationship. Neither Bordin et al. (2013) nor Hopkinson (2007) focused on how a LiDAR sensor works in a typical agricultural field setting. By using data acquired in a test plot with several varieties of crops, the resulting data acquired in this study can be applied to navigation for agricultural robots looking to be used in field settings.

Other studies also used similar field-testing methods to what was conducted in these experiments. Andújar et al. (2013), Rosell et al. (2009), and Weiss and Biber (2011) used LiDAR sensors to distinguish crops. Rosell and their team used a 2D LiDAR and created 3D digitized images of an orchard while Andújar and his team were distinguishing between crops and weeds. Weiss and Biber used the LiDAR sensor to distinguish crops and map the field to improve the localization of the ground robot. All these studies used LiDAR sensors and field testing; however, they did not focus on comparing the relationship between the return intensity of the laser and the distance the laser emission traveled. Understanding the impact of distance on the output of LiDAR sensors will help improve LiDAR's use in agricultural settings.

Many of the studies mentioned previously in Chapter 2.1 about agricultural ground robots had similar ground robot concepts. The ground robots being studied for weed removal by Loukatos et al. (2021) and Quan et al. (2022) both had similar designs to the ground robot used to acquire this data. The two ground robots in those studies are being used for weed removal research. Similarly, the robots being used by Azmi et al. (2021) and Kumar and Ashok (2021) are being used for one research focus. However, the robot used in this study is being applied to not only weed removal but also for autonomous navigation, such as the LiDAR sensor. The robot, Thorvald II, built by Grimstad and From (2017) is also being used for a variety of different settings as it is equipped to deal with different environments. The robot in the study was only built for row field testing but is being applied to many aspects that go into field robots such as navigation, like Gai et al. (2021) and Tu et al. (2019). Navigation is extremely crucial for any ground robot and an important step for autonomous ground robots. The work done in this study is to gain a better understanding of the LiDAR sensor in the process of creating an autonomous robot. As the sensors being utilized for an autonomous robot are better understood, the navigation of the autonomous robot will become simpler. As the study by Malavazi et al. (2018) concluded, navigation of an autonomous robot is possible using a LiDAR sensor. Knowing that- it is important to conduct more research on how a LiDAR sensor behaves in an agricultural setting before fully relying on the sensor as the only navigation tool. However, Malavazi and their team have proven that it is possible to navigate with only one sensor which expands the possibilities for autonomous robots greatly.

4.7.1. Limitations

There were some limitations to this method of data collection. The test plots had a selective number of crops; therefore, a large variety wasn't used. Due to this and the heights chosen, more research would be needed to expand upon the data found in these trials. The trials used were conducted to keep environmental factors as similar as possible. However, it is important to note that changes in these factors – such as sunlight/cloud cover, temperature, or wind, could have had an impact on the data collection. The shorter growing season in northern areas limited the time that this study was able to take place as well. Completing more trials in different weather conditions could help account for some of the influences. This is not taken directly considered in this research as that would expand the scope of what this research is covering. This model and the outcome found were based solely on this experiment. While there were multiple trials for each condition, there was no further experimental research conducted. More trials with more angles and heights used would be the best way to expand this research. As mentioned before, weather conditions and the lack of more trials could have affected the results. More information on these aspects would be important for an improved model.

Another factor that is relevant to note is that as this was conducted in a field setting, the angles and heights were all original measurements. The angle was measured at the beginning and end of each trial and never shifted beyond 1 or 2 degrees from its starting point. The heights measured were taken when the robot was on flat ground. Therefore, those measurements are not consistent throughout the trial due to uneven ground or otherwise jostling the robot. However, these slight variations are unavoidable for field testing and make it more accurate for actual predictions. More trials could also help average the variation due to that as well. They would also be beneficial in determining more about the relationship between the variables looked at in this study. With more trials, there should be clearer evidence of the correlation between the return intensity of the laser beam and the distance the beam traveled from the sensor to the object. Completing more trials for at least one of the conditional setups would illustrate this point more clearly and would be important to consider if continuing to expand upon this topic.

5. CONCLUSION

The relationship that can be determined between the return intensity of the laser beam and the distance the beam traveled will be beneficial to the future use of LiDAR in agriculture. Understanding the impact of how far the sensor is from the object being analyzed will allow for better judgment when determining sensor placement in future experiments. LiDAR sensors can be used for obstacle detection, plant identification, or land mapping. Other settings can also benefit from understanding this relationship. Sensor placement is important for any application and this analysis could help with that. This data was collected using a ground robot and LiDAR sensor. By comparing the results of 3 trials with varying heights and angles for the sensor placement, the relationship between the 2 variables being compared can be more clearly illustrated.

The output of this data showed some contradictions when comparing certain aspects. With the lack of normality in the data, the linear regression and ANOVA tests were skewed. However, it can be determined that it is unlikely that there is a linear relationship in this data set as clearly indicated by the residual plots (Figure 4.7.) and the low R squared values (Table 4.2.). There is most likely not a logarithmic trend in this data either. The ROC curves (Figure 4.8.) and low R squared values (Table 4.4.) in this test are clear indicators. However, the non-parametric Chi-Squared test of the variables, the return intensity of the laser and distance traveled by the laser beam, tells that there is a correlation between the variable but a very low correlation. Collecting more data for further analysis would be beneficial for future studies.

5.1. Future Work

This research opens different possibilities when it comes to expanding the working knowledge of LiDAR sensors. Doing more experimental trials with different heights and angles can allow for a more accurate prediction of the model between these 2 components. Completing more trials for each experimental setup would benefit the analysis of the data as well. Using different environments is another way the model can be improved. Using both a lab and field environment would be helpful to eliminate some of the elements that limited this research such as the limited growing seasons in North Dakota. Finding the optimal sensor height, angle, and distance from the crop can be determined by exploring this relationship more as well. That and other implementations of this research are important to using LiDAR sensors most effectively and efficiently.

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APPENDIX. EXCEL FILE OUTPUT FROM LIDAR SENSOR

Points_m_XYZ:0	Points_m_XYZ:1	Points_m_XYZ:2	X	Y	Z	Intensity	Laser_id	Azimuth	Distance_m	Adjusted time	Time stamp	Vertical_angle
0.017135	0.663196	-0.30936	0.017135	0.663196	-0.30936	12	0	8	0.732	3.38E+08	3.38E+08	-25
-0.04339	0.602347	-0.01054	-0.04339	0.602347	-0.01054	14	1	8	0.604	3.38E+08	3.38E+08	-1
0.019234	0.739437	-0.02153	0.019234	0.739437	-0.02153	34	2	9	0.74	3.38E+08	3.38E+08	-1.667
-0.01418	0.619997	-0.17361	-0.01418	0.619997	-0.17361	12	3	9	0.644	3.38E+08	3.38E+08	-15.639
0.023718	0.905746	-0.18121	0.023718	0.905746	-0.18121	41	4	10	0.924	3.38E+08	3.38E+08	-11.31
-0.01643	0.723814	0	-0.01643	0.723814	0	13	5	10	0.724	3.38E+08	3.38E+08	0
0.064026	0.849533	-0.00992	0.064026	0.849533	-0.00992	28	6	11	0.852	3.38E+08	3.38E+08	-0.667
-0.01984	0.881174	-0.13712	-0.01984	0.881174	-0.13712	22	7	11	0.892	3.38E+08	3.38E+08	-8.843
0.020912	0.793321	-0.10101	0.020912	0.793321	-0.10101	30	8	11	0.8	3.38E+08	3.38E+08	-7.254
-0.04479	0.62639	0.00365	-0.04479	0.62639	0.00365	12	9	11	0.628	3.38E+08	3.38E+08	0.333
0.02313	0.871678	-0.00507	0.02313	0.871678	-0.00507	87	10	12	0.872	3.38E+08	3.38E+08	-0.333
-0.01386	0.620256	-0.06683	-0.01386	0.620256	-0.06683	65	11	12	0.624	3.38E+08	3.38E+08	-6.148
0.057132	0.75455	-0.07064	0.057132	0.75455	-0.07064	21	12	13	0.76	3.38E+08	3.38E+08	-5.333
-0.01861	0.839566	0.019541	-0.01861	0.839566	0.019541	54	13	13	0.84	3.38E+08	3.38E+08	1.333
0.066892	0.881405	0.010291	0.066892	0.881405	0.010291	20	14	14	0.884	3.38E+08	3.38E+08	0.667
-0.01299	0.590415	-0.0413	-0.01299	0.590415	-0.0413	7	15	14	0.592	3.38E+08	3.38E+08	-4
0.018872	0.697424	-0.05696	0.018872	0.697424	-0.05696	58	16	15	0.7	3.38E+08	3.38E+08	-4.667
-0.06523	0.921302	0.02688	-0.06523	0.921303	0.02688	33	17	15	0.924	3.38E+08	3.38E+08	1.667
0.023583	0.871548	0.015218	0.023583	0.871548	0.015218	10	18	15	0.872	3.38E+08	3.38E+08	1
-0.04229	0.597276	-0.03837	-0.04229	0.597276	-0.03837	36	19	15	0.6	3.38E+08	3.38E+08	-3.667
0.057983	0.7605	-0.04442	0.057983	0.7605	-0.04442	25	20	16	0.764	3.38E+08	3.38E+08	-3.333
-0.01996	0.922221	0.05372	-0.01996	0.922221	0.05372	56	21	16	0.924	3.38E+08	3.38E+08	3.333

APPENDIX. EXCEL FILE OUTPUT FROM LIDAR SENSOR

0.026609	0.97083	0.039567	0.026609	0.97083	0.039567	23	22	17	0.972	3.38E+08	3.38E+08	2.333
-0.01287	0.599212	-0.02792	-0.01287	0.599212	-0.02792	28	23	17	0.6	3.38E+08	3.38E+08	-2.667
0.020376	0.738705	-0.03873	0.020376	0.738705	-0.03873	12	24	18	0.74	3.38E+08	3.38E+08	-3
-0.02409	1.131246	0.138931	-0.02409	1.131246	0.138931	31	25	18	1.14	3.38E+08	3.38E+08	7
0.026549	0.956449	0.07811	0.026549	0.956449	0.07811	18	26	19	0.96	3.38E+08	3.38E+08	4.667
-0.04109	0.586074	-0.02394	-0.04109	0.586074	-0.02394	33	27	19	0.588	3.38E+08	3.38E+08	-2.333
0.066245	0.860929	-0.03015	0.066245	0.860929	-0.03015	18	28	20	0.864	3.38E+08	3.38E+08	-2
-0.02751	1.313371	0.351994	-0.02751	1.313371	0.351994	24	29	20	1.36	3.38E+08	3.38E+08	15
0.032413	1.16041	0.211655	0.032413	1.16041	0.211655	10	30	20	1.18	3.38E+08	3.38E+08	10.333
-0.01206	0.575718	-0.0134	-0.01206	0.575718	-0.0134	7	31	20	0.576	3.38E+08	3.38E+08	-1.333
0.019131	0.652261	-0.30429	0.019131	0.652261	-0.30429	12	0	28	0.72	3.38E+08	3.38E+08	-25
-0.04129	0.602495	-0.01054	-0.04129	0.602495	-0.01054	10	1	28	0.604	3.38E+08	3.38E+08	-1
0.022051	0.747358	-0.02176	0.022051	0.747358	-0.02176	34	2	29	0.748	3.38E+08	3.38E+08	-1.667
-0.01201	0.620042	-0.17361	-0.01201	0.620042	-0.17361	12	3	29	0.644	3.38E+08	3.38E+08	-15.639
0.026879	0.905658	-0.18121	0.026879	0.905658	-0.18121	27	4	30	0.924	3.38E+08	3.38E+08	-11.31
-0.01413	0.735864	0	-0.01413	0.735864	0	9	5	30	0.736	3.38E+08	3.38E+08	0
0.066843	0.849316	-0.00992	0.066843	0.849316	-0.00992	25	6	30	0.852	3.38E+08	3.38E+08	-0.667
-0.01639	0.853573	-0.13282	-0.01639	0.853573	-0.13282	22	7	30	0.864	3.38E+08	3.38E+08	-8.843
0.023681	0.793243	-0.10101	0.023681	0.793243	-0.10101	18	8	31	0.8	3.38E+08	3.38E+08	-7.254
-0.04315	0.634524	0.003696	-0.04315	0.634524	0.003696	10	9	31	0.636	3.38E+08	3.38E+08	0.333
-0.01222	0.648135	-0.06983	-0.01222	0.648135	-0.06983	61	11	32	0.652	3.38E+08	3.38E+08	-6.148
0.061653	0.778168	-0.07287	0.061653	0.778168	-0.07287	20	12	33	0.784	3.38E+08	3.38E+08	-5.333
-0.01583	0.847623	0.019727	-0.01583	0.847623	0.019727	58	13	33	0.848	3.38E+08	3.38E+08	1.333

APPENDIX. EXCEL FILE OUTPUT FROM LIDAR SENSOR

0.071235	0.897115	0.010477	0.071235	0.897115	0.010477	19	14	34	0.9	3.38E+08	3.38E+08	0.667
-0.01078	0.582478	-0.04074	-0.01078	0.582478	-0.04074	7	15	34	0.584	3.38E+08	3.38E+08	-4
0.021793	0.713293	-0.05826	0.021793	0.713293	-0.05826	58	16	35	0.716	3.38E+08	3.38E+08	-4.667
-0.06175	0.917535	0.026763	-0.06175	0.917535	0.026763	42	17	35	0.92	3.38E+08	3.38E+08	1.667
0.026381	0.863465	0.015079	0.026381	0.863465	0.015079	9	18	35	0.864	3.38E+08	3.38E+08	1
-0.03994	0.593437	-0.03812	-0.03994	0.593437	-0.03812	36	19	35	0.596	3.38E+08	3.38E+08	-3.667
0.06286	0.788158	-0.04605	0.06286	0.788158	-0.04605	34	20	36	0.792	3.38E+08	3.38E+08	-3.333
-0.01682	0.926278	0.053953	-0.01682	0.926278	0.053953	56	21	36	0.928	3.38E+08	3.38E+08	3.333
0.030491	0.98671	0.040219	0.030491	0.98671	0.040219	23	22	37	0.988	3.38E+08	3.38E+08	2.333
-0.01077	0.599253	-0.02792	-0.01077	0.599253	-0.02792	25	23	37	0.6	3.38E+08	3.38E+08	-2.667
0.022954	0.738629	-0.03873	0.022954	0.738629	-0.03873	12	24	38	0.74	3.38E+08	3.38E+08	-3
-0.02007	1.127354	0.138444	-0.02007	1.127354	0.138444	33	25	38	1.136	3.38E+08	3.38E+08	7
0.029887	0.95635	0.07811	0.029887	0.95635	0.07811	18	26	39	0.96	3.38E+08	3.38E+08	4.667
-0.03904	0.586214	-0.02394	-0.03904	0.586214	-0.02394	31	27	39	0.588	3.38E+08	3.38E+08	-2.333
0.068608	0.852723	-0.02987	0.068608	0.852723	-0.02987	15	28	40	0.856	3.38E+08	3.38E+08	-2
-0.02272	1.30187	0.348888	-0.02272	1.30187	0.348888	24	29	40	1.348	3.38E+08	3.38E+08	15
0.036169	1.144551	0.208785	0.036169	1.144551	0.208785	9	30	41	1.164	3.38E+08	3.38E+08	10.333
-0.01009	0.583755	-0.01359	-0.01009	0.583755	-0.01359	7	31	41	0.584	3.38E+08	3.38E+08	-1.333
0.02117	0.644944	-0.3009	0.02117	0.644944	-0.3009	12	0	48	0.712	3.38E+08	3.38E+08	-25
-0.03944	0.606627	-0.01061	-0.03944	0.606627	-0.01061	10	1	48	0.608	3.38E+08	3.38E+08	-1
0.024264	0.735288	-0.02141	0.024264	0.735288	-0.02141	34	2	49	0.736	3.38E+08	3.38E+08	-1.667
-0.00967	0.608526	-0.17037	-0.00967	0.608526	-0.17037	12	3	49	0.632	3.38E+08	3.38E+08	-15.639
0.030431	0.917319	-0.18357	0.030431	0.917319	-0.18357	27	4	50	0.936	3.38E+08	3.38E+08	-11.31
-0.0115	0.73191	0	-0.0115	0.73191	0	9	5	50	0.732	3.38E+08	3.38E+08	0

APPENDIX. EXCEL FILE OUTPUT FROM LIDAR SENSOR

0.069479	0.845091	-0.00987	0.069479	0.845091	-0.00987	22	6	50	0.848	3.38E+08	3.38E+08	-0.667
-0.01322	0.841769	-0.13098	-0.01322	0.841769	-0.13098	24	7	50	0.852	3.38E+08	3.38E+08	-8.843
0.026847	0.805053	-0.10253	0.026847	0.805053	-0.10253	18	8	51	0.812	3.38E+08	3.38E+08	-7.254
-0.0417	0.646646	0.003766	-0.0417	0.646646	0.003766	10	9	51	0.648	3.38E+08	3.38E+08	0.333
0.029349	0.875493	-0.00509	0.029349	0.875493	-0.00509	7	10	52	0.876	3.38E+08	3.38E+08	-0.333
-0.01277	0.831094	-0.08953	-0.01277	0.831094	-0.08953	31	11	52	0.836	3.38E+08	3.38E+08	-6.148
0.06634	0.801763	-0.0751	0.06634	0.801763	-0.0751	17	12	53	0.808	3.38E+08	3.38E+08	-5.333
-0.01287	0.847673	0.019727	-0.01287	0.847673	0.019727	61	13	53	0.848	3.38E+08	3.38E+08	1.333
0.073374	0.884903	0.010337	0.073374	0.884903	0.010337	16	14	54	0.888	3.38E+08	3.38E+08	0.667
-0.00874	0.582512	-0.04074	-0.00874	0.582512	-0.04074	9	15	54	0.584	3.38E+08	3.38E+08	-4
0.025639	0.753057	-0.06151	0.025639	0.753057	-0.06151	58	16	55	0.756	3.38E+08	3.38E+08	-4.667
-0.05778	0.905775	0.026414	-0.05778	0.905775	0.026414	45	17	55	0.908	3.38E+08	3.38E+08	1.667
0.029531	0.867365	0.015149	0.029531	0.867365	0.015149	9	18	55	0.868	3.38E+08	3.38E+08	1
-0.03939	0.617476	-0.03965	-0.03939	0.617476	-0.03965	34	19	55	0.62	3.38E+08	3.38E+08	-3.667
0.066273	0.795892	-0.04651	0.066273	0.795892	-0.04651	28	20	56	0.8	3.38E+08	3.38E+08	-3.333
-0.01358	0.926331	0.053953	-0.01358	0.926331	0.053953	53	21	56	0.928	3.38E+08	3.38E+08	3.333
0.035309	1.026541	0.041847	0.035309	1.026541	0.041847	61	22	57	1.028	3.38E+08	3.38E+08	2.333
-0.00897	0.619263	-0.02885	-0.00897	0.619263	-0.02885	25	23	57	0.62	3.38E+08	3.38E+08	-2.667
0.025532	0.738545	-0.03873	0.025532	0.738545	-0.03873	12	24	58	0.74	3.38E+08	3.38E+08	-3
-0.01602	1.119477	0.137469	-0.01602	1.119477	0.137469	31	25	58	1.128	3.38E+08	3.38E+08	7
0.034471	0.992099	0.081039	0.034471	0.992099	0.081039	18	26	59	0.996	3.38E+08	3.38E+08	4.667
-0.03775	0.598313	-0.02442	-0.03775	0.598313	-0.02442	30	27	59	0.6	3.38E+08	3.38E+08	-2.333
0.069912	0.832561	-0.02918	0.069912	0.832561	-0.02918	13	28	60	0.836	3.38E+08	3.38E+08	-2

APPENDIX. EXCEL FILE OUTPUT FROM LIDAR SENSOR

-0.01818	1.301941	0.348888	-0.01818	1.301941	0.348888	24	29	60	1.348	3.38E+08	3.38E+08	15
0.040302	1.14835	0.209503	0.040302	1.14835	0.209503	10	30	61	1.168	3.38E+08	3.38E+08	10.333
-0.00838	0.607778	-0.01414	-0.00838	0.607778	-0.01414	7	31	61	0.608	3.38E+08	3.38E+08	-1.333
0.023421	0.644866	-0.3009	0.023421	0.644866	-0.3009	12	0	68	0.712	3.38E+08	3.38E+08	-25
-0.03708	0.602769	-0.01054	-0.03708	0.602769	-0.01054	10	1	68	0.604	3.38E+08	3.38E+08	-1
0.028726	0.787143	-0.02292	0.028726	0.787143	-0.02292	51	2	69	0.788	3.38E+08	3.38E+08	-1.667
-0.00764	0.616259	-0.17253	-0.00764	0.616259	-0.17253	12	3	69	0.64	3.38E+08	3.38E+08	-15.639

Note: This is 100 lines of the data collected from Condition 1 – Trial 1 – Frame 1556. There are 33048 lines of data from this single frame.