DESIGN AND DEVELOPMENT OF 3D POINT CLOUD SCANNER SYSTEM (3D-PCSS) BASED ON 2D LIDAR WITH A WEB-BASED APPLICATION FOR FLOUR PRODUCT STORAGE VOLUME MEASUREMENT

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CHAPTER I

INTRODUCTION

1.1 Background of the Study

Agricultural raw materials, such as rice, wheat, and corn, which mostly include solid, liquid or powered, provide significant amounts of carbohydrates for use in industry and human nutrition . Certain grains require little processing and can be eaten right away after harvest, while others must be prepared through a number of primary and secondary milling steps. As farmers learned to produced more resulting of various agricultural innovation, this raw materials must preserve the quality for future consumption (Bucklin et al., 2019). It is expected an increase in raw materials annually does necessitate an efficient post-harvest processes such as raw product storing method incorporating modern technologies (Yegorova et al., 2021).

Various tools and methods have been developed to measure stored raw materials volume inside an industrial storage silos or bins, employing sensors like contact level indicators (e.g., tilt switches, pressure diaphragms, rotary paddles) and non-contact indicators (e.g., stereovision, radar, ultrasound, lasers). Contact sensors offer cost-effective, dust-resistant point measurements but lack surface detail. Non-contact sensors can map grain surfaces accurately but require permanent mounting, are relatively expensive, and are susceptible to dust interference. However, conventional volumetric measurement method using weighted fiberglass tape is still being used providing only a single data point which leads to inaccuracy and error-prone volume measurement (Turner et al., 2017).

Point cloud data consists of a set of points representing an object in either a two or three-dimensional structure. This data typically comprises X, Y, and Z coordinates, but modern point clouds may also include additional information such as intensity, RGB values, and more (Wang and Kim, 2019; Stojanovic, 2023).

Light Detection and Ranging (LiDAR) is one of the many devices that can gather 3D points that often refer as point clouds. Unfortunately, commercial 3D LiDAR systems tend to be expensive in comparison to their 2D-based LiDAR. This cost disparity can lead to limitations in accessibility for certain applications or industries, hindering widespread adoption and innovation in fields where 3D spatial data is crucial. Low-cost two axes-based LiDAR can mimic the collection of 3D point cloud by adding an additional axes using tilting device (Clar and Salaan, 2022). However, it comes with a notable drawback: it lacks several capabilities present in high-end 3D LiDAR systems, including multi-echo functionality, long-range detection, high angular resolution, among others.

Recent innovations in various industries have made the production less manual but producing more by using automation and wireless technologies that helped to produce better and accurate measurement compared to traditional methods. These approaches include various sensing technologies, automated measurements, machine to machine (M2M) communications, and monitoring systems. The interconnected sensors and actuators allow to remotely collect data, store, and process the data to provide better insight in the industry and also for the economic growth, specify the characteristics of a paperless factory, it is a development of a smart factory in which all data that is turned into information is stored, transferred, and displayed entirely remotely and digitally. As the level of digitization of a smart factory, it is not a revolution but rather an evolution (Bulut et al., 2020).

1.2 Statement of the Problem

While some food manufacturing industries still rely on manual and labor-intensive storage measurement procedures, there is a growing need to adopt advanced technologies with remote capabilities. This shift aims to eliminate the need for frequent physical processes that may endanger employees. Silo storage systems are versatile, accommodating a wide range of products, including solids, powders, and liquids. One characteristic of product storages is that when they are filled with raw materials, except for liquids, they create a dust cloud in the empty space. Solid grains like corn typically produce minimal dust clouds during filling, whereas powdered substances like cement or flour often generate dense dust clouds.

When implementing LiDAR for storage volume measurement, the ideal placement is at the top of the silo. However, in the case of fine-textured solid materials such as flour, dispersed dust clouds may arise during the pneumatic conveying process of loading flour into the bin (Williams and Rosentrater, 2007). Although LiDAR sensors offer advantages such as rapid data collection and precise spatial representation compared to alternative sensing technologies, their operational wavelengths—usually between 700 to 900 nm—can pose challenges when scanning through layers of dust deposited by stored products. This challenge may potentially impact the accuracy of spatial structure scans.

This study presents the development of a 3D point cloud scanner system for volume measurement of flour storage. The system is designed to be controlled and scanned remotely, alleviating the manual process of volume measurement. Additionally, this study investigates the behavior of the system when dust clouds are present during filling.

1.3 Objectives of the Study

The general objective of this study was to develop a system that can remotely measure the volume of the product inside of a flour storage bin using point cloud data and Web-based Application. The following specific goals were completed:

1. Designed and developed a 3D point cloud scanner system (3D-PCSS);
2. Developed a web-based application for remote access and visualization of the system;
3. Tested and evaluated the performance of the system.

1.4 Originality of the Study

The originality of this study lies in the development of a system capable of remotely estimating and monitoring the volume and capacity of storage materials. This study introduces two distinct components: the point cloud acquisition system and the web application system designed for remote monitoring purposes. Furthermore, the study explores the system's behavior in the presence of dust, providing insights for further enhancement and modification.

1.5 Scope and Limitations

The scope of this study is to develop a volume estimation system through remote point cloud acquisition and a web application. It is important to note that the system testing was not conducted directly in a commercial manufacturing industry or an actual industrial storage bin. Instead, testing took place in an open area using a mock-up storage bin designed to replicate the size and shape of a typical industrial storage facility. Additionally, the study exclusively focuses on utilizing flour as the primary raw material for testing purposes.

1.6 Significance of the Study

Accurate and efficient post-harvest processes are vital in the food industry to ensure effective inventory management and maintain an adequate supply of materials. Automation with remote sensing devices is a modern technology that can be integrated into a variety of industries, eliminating labor-intensive tasks that may expose employees to dangerous scenarios. The development of the 3D point cloud scanner system (3D-PCSS) addresses the need for precise volume measurement of stored flour within silo storage bins. By employing point cloud data and a web-based application, the system offers remote accessibility and visualization capabilities, allowing for convenient monitoring and management of storage facilities. This technological advancement, with potential integration into industrial settings, not only enhances efficiency in inventory management but also minimizes the risks associated with manual measurement procedures. Furthermore, the testing and evaluation of the system provide valuable insights into its performance and potential for further refinement, paving the way for future advancements in automated storage volume measurement systems.

1.7 Conceptual Framework

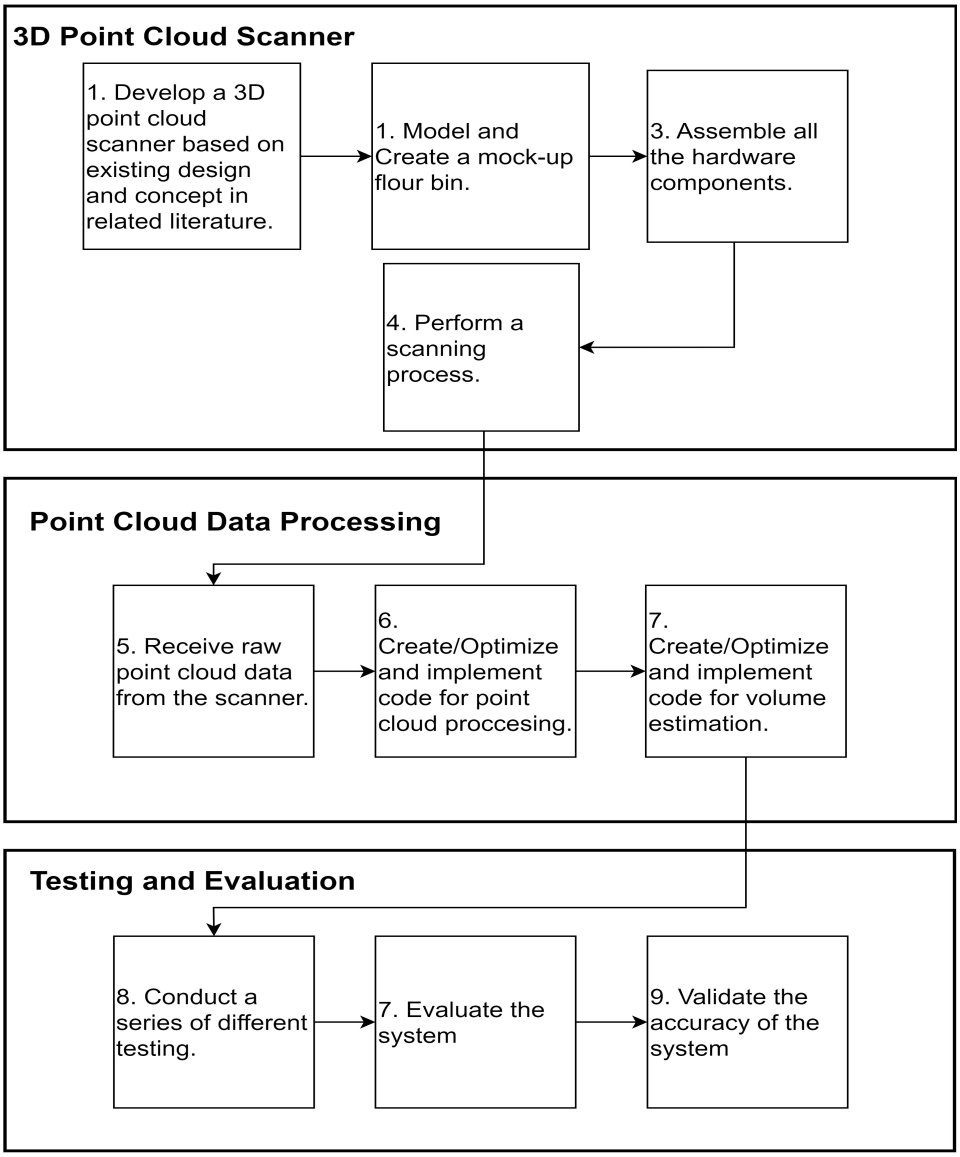

Figure 1.1. General Conceptual Flow

1.8 Theoretical Framework

The research is based on the idea of using automation for industrial operations, specifically in the food industry. Point cloud data is a collection of an unorganized set of x, y, and z coordinates in a three-dimensional space. There are various ways to acquire point cloud data, and one possible way is through active non-contact sensing technology such as LiDAR sensor. LiDAR uses Time-of-Flight (TOF) method of measuring distance between the sensor to the object. TOF scanners are inexpensive compared to other specialized 3D scanners (Chua et al., 2017). The researcher will utilize LiDAR to acquire 3D point cloud data because of its ability to gather points data and converts them into a global world coordinate frame (Bi et al., 2021). The study does, however, acknowledge the potential limits of LiDAR, when the environment is prone to medium (e.g., water vapor, gases, dust particle, etc.) that can obstruct the target surface, the LiDAR acquired point cloud data that may alter the precision of the data (Chua et al., 2017). Thus, the researcher will manage the raw point cloud data by filtering the factoring medium such as dust. Lastly, Delaunay Triangulation is a computational geometry computation that connects a set points to form a mesh of triangles. It can be used for volume estimation by calculating the volume of a convex hull which will be use in this study.

1.9 Definition of Terms

1. **LiDAR** —stands for Light Detection and Ranging, can also be describe as Light Imaging, Detection, and Ranging. It is a method for determining ranges by targeting an object or a surface with a laser and measuring the time-of-flight to determine the distance.

2. **Bin** —is a large container used to store materials, such as grain, coal, sand, or other bulk goods. They are typically made of metal, plastic, or wood and come in various sizes, shapes, and designs.

3. **ROS** —Robot Operating System is a set of open-source libraries and tools designed to help developers build robot applications. It provides

a common framework for creating, managing and sharing code, data, and other resources related to robotic systems.

4. **Point Cloud** —is a set of data points in a three-dimensional space, typically representing the surface of an object. Each point in the cloud is defined by its three-dimensional coordinates (x, y, and z) and may also include additional information such as color, intensity, or normal vector.

5. **Convex Hull** —is the minimum convex polygon from the set of points that encompasses all of the points in the set.

CHAPTER II

REVIEW OF RELATED LITERATURE

In this chapter, the researcher discussed the general idea of the volume estimation and filtering method and its several related studies. The chapter also presented some published and unpublished methods and technologies used for measuring the level and volume of the materials inside the silo (or sometimes called bin).

Several traditional level measurements are already used and studied in different industries such as weight and cable methods, ultrasonic, Guided Ware Radar (GWR), and Thru-air Radar (TAR) which has their own advantage and disadvantages. Ultrasonic and laser technologies are excellent in providing accurate and detailed measurement of level. However, these technologies are problematic when in terms of dusty environment (Duysak and Yigit, 2020).

2.1 3D Point Cloud Acquisition

The recent advancements in spatial acquisition technologies such as aerial or terrestrial laser scanning have resulted in the formation of point clouds that may contain millions, billions, or trillions of points (Jaboyedoff et al., 2012). Various 3D scanning technology produces data that are formatted as point cloud, typically these point cloud data acquired using laser or image scanner. These gathered data can be managed to ease the measurement and visualization of an object or environment (Chua et al., 2017). Point cloud data are processed to generate desired output on the specific application. Over the past 20 years, the advent of high-quality 3D point cloud acquisition changes the perspective of robotics. Moreover, 3D scanning through various technologies enable the possibility of less contact for physical measurement that eliminate the traditional approach that involves time and effort. Unfortunately, most of these 3D sensors are expensive and therefore various relevant projects are considering not to use these sensors and opt to utilize alternative technology (Rusu and Cousins, 2011).

2.1.1 Light Detection and Ranging (LiDAR)

LiDAR is a remote sensing technology that uses laser light to create precise 2D or 3D models of objects or environments. LiDAR systems emit laser pulses that bounce back from objects in the environment, and the time taken for the light to return is used to determine the distance between the object and the sensor which called Time-of-Flight (ToF). By combining the distance measurements from multiple laser pulses, a point cloud can be generated that represents the shape and structure of the objects in the environment, Figure 2.2 shows the block diagram of a typical LiDAR system. LiDAR technology have been used in industrial settings. In the context of LiDAR scanning, individual point cloud scans are acquired and processed for a specific area. These point clouds are then merged and blended together to generate a complete point cloud of the desired area, which can be utilized for distance and measurement calculations (Jaboyedoff et al., 2012; Raj et al., 2020).

A 360-degree scan of a LiDAR is generally obtained in figure 2.1 to produce a 2D map, a typical scan using the robot's top-mounted 2D LIDAR. The axis of the rotating LIDAR sensor is shown as a red line. The border of the surrounding obstacles is indicated in blue (Sarker et al., 2020).

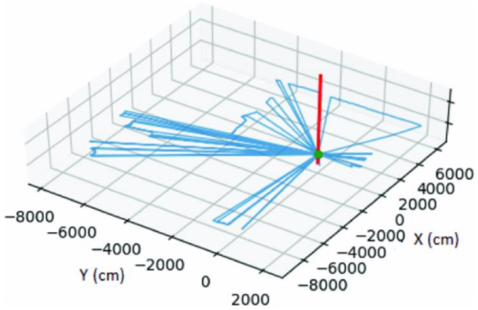

Figure 2.1. 360-degree scan of 2D LiDAR

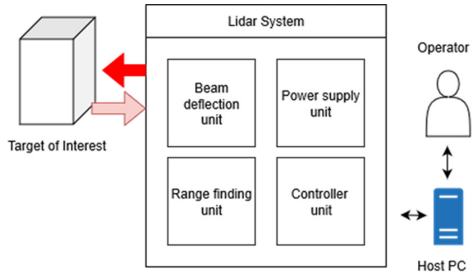

Figure 2.2. Typical LiDAR System

Kang et al. (2018) utilized a 2D low-cost off-the-shelf LiDAR to reconstruct complex 3D model by integrating an external rotary for additional dimension. The experimental test achieved to evaluate 3D reconstruction by concluding that using a low-cost 2D LiDAR sensors can perform 3D point cloud acquisition but increase either the complexity of its hardware or software. Figure 2.3 illustrate the principle of 3D concept based on moving 2D LiDAR with 2 fixed different position in a room, the world coordinate frame is denote as $W - X_W Y_W Z_W$. Although moving 2D LiDAR can never replace commercial 3D LiDAR with several reasons especially with applications involving real-time performance, however, moving 2D LiDAR can be partially used and installed with in terms of static and nonmoving environment (Bi et al., 2021).

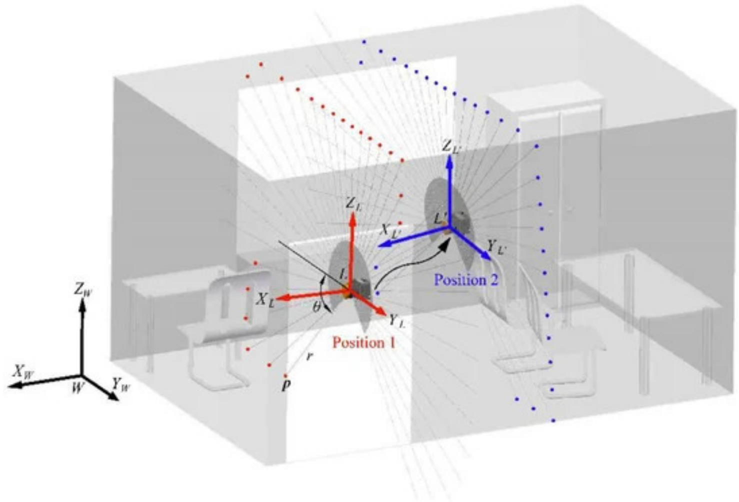

Figure 2.3. The principle of moving 2D LiDAR

2.2 Point Cloud Processing

Recent advancements in 3D reconstruction and visualization based on point cloud data have led to rapid development in various fields due to the rich data information and detailed real-world representation of objects or environments. Consequently, this massive data, including enormous kinds of noise, is overwhelmingly tedious to manage (Li et al., 2020).

In the study conducted by Wang et al. (2020), when point cloud data are involved in construction applications, different point cloud data processing procedures are crucial to achieving desired outputs. Figure 2.4 shows the common procedures for the raw point cloud data in a construction setting (Wang et al., 2020).

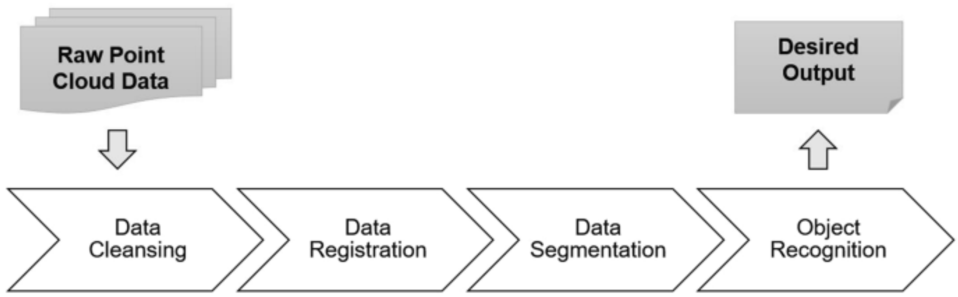

Figure 2.4. Typical processing procedures of point cloud data

Stanislas et al. (2021) divided the point cloud processing into four-step processes, figure 2.5 illustrates the structure of the authors, the point cloud output of the method is the same point cloud that was inputted before the classification took place. The method involves feature computing, data formatting, network prediction, and post-processing.

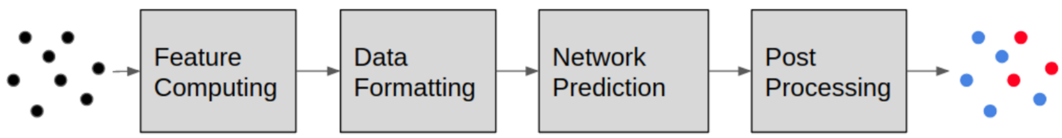

Figure 2.5. The four stages of the point cloud classification process

2.2.1 Outlier Point Cloud Processing

Processing of point cloud data by filtering is intensively exposed in research with a wide variety of applications. Cleaning of raw 3D point clouds is commonly the first step for most geometry processing, it involves removing the outliers (e.g., dust, snow, fog, etc.) after classifying the dust and non-dust (inliers) point cloud, smoothing the remaining data, and then reconstructing the surface into a three-dimensional representation (Rakotosaona et al., 2020). Artificial Intelligence techniques such as Machine Learning (ML) and Deep Learning (DL) are widely used in classifying point cloud dust and non-dust data to remove noise.

For instance, Stanislas et al. (2018) detected dusty regions in point cloud data by using machine learning techniques as well as specialized neural networks. The 3D map was transformed into 3D occupancy grids in this investigation, and the occupied voxels were utilized to train classifiers based on machine learning to extract significant information, figure 2.6 shows the result of the study.

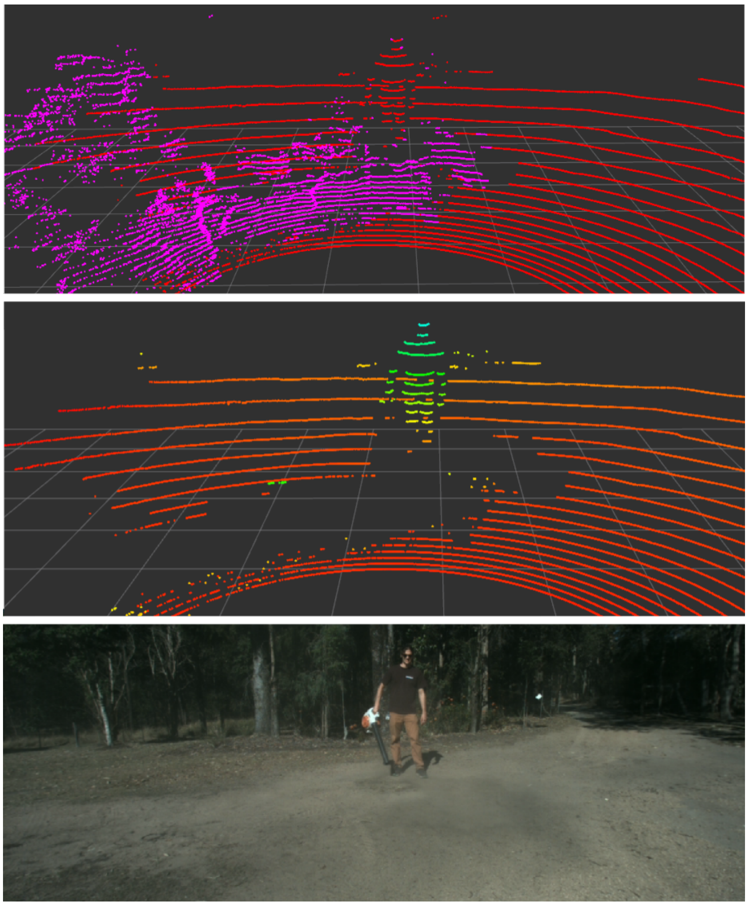

Figure 2.6. Top: Detection of airborne dust particle in a LiDAR point cloud, purple is Particle and red is Non-particle. Middle: Removal of detected dust particles from point cloud for robust perception, the color is mapped to the vertical axis (red is low, green is high). Bottom: Image depicting the scene.

The same voxel-based approach was also used in the study of Shamsudin (2016) for the classification of fog. The method involved using geometrical features and intensity as inputs for the support vector machine (SVM) and k-nearest neighbors (KNN) algorithms to classify fog.

Both point- and voxel-based categorization were taken into account in study by Stanislas et al. (2021). They experimented with various classifier input features to determine the most effective one for dust removal in order to boost performance. These characteristics include geometry, intensity, and multi-echo data from the LiDAR sensor. With point-based deep learning techniques, geometry, and multi-echo features proved to be the most useful features, while voxel-based deep learning techniques benefited from the addition of intensity information to these features.

To simplify the point cloud models and reduce the noise in point cloud data, Zhu et al. (2020) employed the point-based simplification and guided filter. The guided filter was employed to filter the noisy point cloud model and generate the filtered image. The surface-based filtering group employs the filtering algorithm.

Ramiya et al. (2017) set a threshold by measuring the distance between every point and the mean surface. They assigned a weight to each point based on its distance from the interpolated mean surface.

Heinzler et al. (2020) used a large point cloud data set for CNN-based approach segmentation in controlled adverse weather effects. The approach takes a global understanding of the scene to estimate the validity of individual point measurements, rather than analyzing local spatial statistics as in previous approaches, it also proposes data augmentation technique that reduces the necessity for annotated ground truth data.

The multi-echos and intensity data features of LiDAR point cloud are utilized in various studies. Afzalaghaeinaeini et al. (2021) used low-intensity outlier removal (LIOR) filtering for de-dusting method. The method is composed of two procedures: First, dust particles based on point cloud usually have a lower intensity compared to non-dust point cloud, point cloud with an intensity lower than the set threshold are removed. Second, the study successfully filtered the point cloud data and removed the dust from the original point cloud data.

Intensity-based filter was also utilized by Park et al. (2020) for removal of snow in point cloud data. The study concluded that this method overcomes the disadvantages of LiDAR sensor compared to other conventional filtering methods.

2.2.2 3D Space Point Cloud Mapping

In todays generation, various point cloud processing and mapping frameworks are widely available to lessen the complexity of handling raw point cloud data, such as, Robotic Operating System (ROS), Point Cloud Library (PCL), Open3D, MeshLab, etc. Most of this framework can be used in many different fields such as virtual reality, construction, industry, and surveying.

The PCL has a built-in visualization library that uses Visualization ToolKit (VTK) as its foundation. VTK is a versatile platform that can render 3D point clouds and surfaces, and supports visualizing tensors, textures, and volumetric methods. The PCL Visualization library aims to merge PCL with VTK by providing a complete visualization layer for n-D point cloud structures. Its main goal is to allow for rapid prototyping and visualization of algorithm results on high-dimensional data (Rusu and Cousins, 2011).

Ocando et al. (2017) take advantage of using ROS framework to map the 3D point cloud data, as the framework allows to interlink programs that is written in different languages. The study successfully addressed the problematic tasks of Simultaneous Localization and Mapping (SLAM) and 3D Octomapping via single sensor.

2.3 Volume Estimation

Typically in an agriculture and food company setting, calculating the volume of a storage bin involves determining both the storage geometry and the distance between the grain surface and the eave. Traditionally, a fiberglass tape measure with weights is used to calculate the distance between the surface of the grain and the top of the bin. Correction factors are applied to the measurement to account for any irregularities in the surface of the grain, such as when the surface is uneven or when there is a cone-shaped pile (Turner et al., 2016). These correction factors are usually simple to apply when the surface is relatively flat and equal in height. Moreover, these traditional approaches necessitate such effort and involved the employees to be at the top of the bin during the estimation. New methods and technologies have been trying to incorporate in industrial settings to eliminate these traditional methods such as using Microwaves Radar (Vogt and Gerding, 2017), Horn Antennas-based (Duysak and Yigit, 2020; Yigit et al., 2015), Load Cell, Ultrasonic, Laser-based (Guevara et al., 2020), and Temperature-based sensor (Rhee et al., 2021). Each of this technology has their own advantage and disadvantages, however, laser-based sensor (e.g. LiDAR) shows an interesting capabilities and features especially in acquiring three-dimensional point cloud data that can be used for geometric computation and for 3D object representation.

Point clouds in 3D are highly valuable as they contain crucial information on the shape, size, area, and volume of objects. Various industries, including agriculture and fisheries, have effectively utilized volume estimating methods based on point clouds (Guevara et al., 2020).

In computer graphics, a voxel is an image that depicts a specific region that has been partitioned into a grid of cubes that are all the same size and uniformly spaced (Putman and Popescu, 2018).

Due to a better portrayal of the region encompassed in the group of points, the Delaunay triangulation and voxelization procedures outperform in estimating the outcomes. These strategies, however, have a greater computational cost because of their accuracy (Auat Cheein et al., 2015). To estimate volume, methods such as Delaunay triangulation and voxelization are used. It is important to consider both accuracy and computing costs when using these methods. Height grids are faster for computing height discrepancies, but accuracy depends on precise point acquisition (Bewley et al., 2011; Duff, 2000).

The Delaunay triangulation-based technique for volume computation, known as Delaunay triangulation-driven volume calculation (DTVC), differs from traditional approaches which computes the volume during the triangulation process rather than preserving Delaunay triangles. This method reduces both memory usage and processing time. Experimental findings demonstrate that DTVC achieves a satisfactory trade-off between precision and efficiency (Liu and Zheng, 2021).

Table 2.1 shows the percentage error analysis from the computed volume of different model point cloud objects in the study of Chang et al. (2017), which shows that in order to estimate the volume of a shape represented by a point cloud, the area of each slice of the shape is calculated by finding the difference between the top and bottom curves of the slice. The total volume of the shape is then calculated by integrating the areas of all the slices using an integration interval equal to the length of the point cloud.

Table 2.1. Point Cloud Volume of Different Model

Objects	True Value (mm^3)	Estimated Value (mm^3)	Error (%)
Cube	1 000 000	1 000 000	0
Cylinder	125.664	125.061	0.479
Sphere	4 188 90.2	4 178 966.87	0.234
Triangle Prism	17.321	17.399	0.45

The study conducted by Jeong et al. (2018) introduces a newly developed explicit hybrid numerical methodology for 3D volume reconstruction from unorganized point clouds, which is based on a modified Allen-Cahn equation and a 3D binary picture segmentation method. The technique has demonstrated potential in a variety of practical applications, including 3D model printing from dispersed scanned data. The computational findings show that the suggested approach for reconstructing 3D volume from point clouds is very efficient and resilient.

The Convex Hull is another method that is popular technique for measuring volume from 3D point cloud points (see figure 2.7). The computational geometry community has extensively studied the convex hull problem, as evidenced by the works of Kim (2002), Graham and Frances Yao (1983), and Maus (1984). Qhull is a commonly used algorithm to compute the convex hull, employing the Voronoi diagram, the Delaunay triangulation, furthest-site Voronoi diagram, the furthest-site Delauney triangulation, and the half-space intersection around a point. The software program allows the creation of high-dimensional objects, and the Quickhull algorithm, written in C, is used to compute the convex hull, which solves round-off errors in floating-point arithmetic. The program is capable of calculating volumes, surface areas, and convex hull approximations.

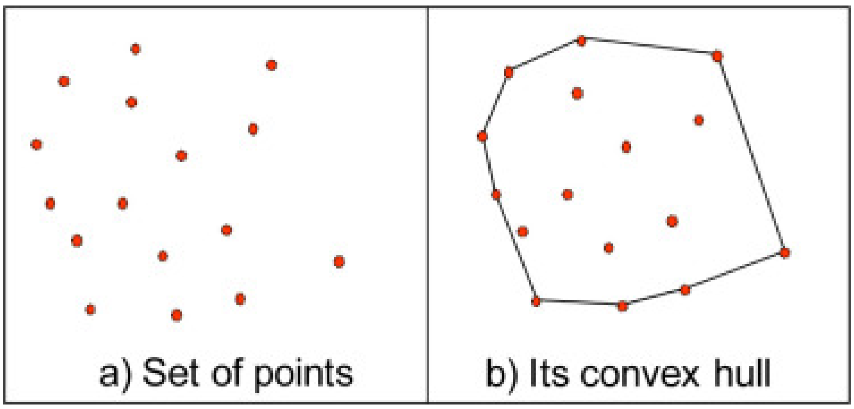

Figure 2.7. Convex Hull

2.4 Synthesis of the Study

The review of related literature conducted and summarized by the researcher are pertinent to guide the researcher in order to achieve the objectives of the study. The review identifies the need for different point cloud data processing procedures to achieve desired outputs. The review also highlights various point cloud processing techniques such as, machine learning (ML), and deep learning (DL) techniques for removing noise and classifying point cloud dust and non-dust data, however, the challenges of these AI approaches with point cloud data for filtering is the amount of data that will be stored for the training method which necessitate millions of point clouds. Another is the high computational cost of these training methods. Lastly, the performance of the method is significantly dependent on its datasets.

While several studies have explored the use of various classifier input features to remove noise, the most effective features have been found to be geometry, intensity, and multi-echo data from the LiDAR sensor. However, there is a gap in the study regarding the evaluation of the performance of these techniques in real-world applications. The need for further research with regard to these methods in a real-world scenarios is highly significant. Thus, this study will address the gap mentioned by integrating these techniques into a real-world applications and identify their practical implications.

CHAPTER III

METHODOLOGY

In this chapter, the researcher will discuss the materials, methods, and flow that will be using and implementing in the study. First, the researcher will discuss the 3D point cloud scanner. Second, the pre-processing and filtering method of point cloud data will be discussed along with the volume estimation method. Lastly, different testing and evaluation of the study will be addressed. Figure 3.1 shows general flowchart of the system.

3.1 3D Point Cloud Scanner

The researcher will adopt the concept of tilting method using a 2D of-the-shelf LiDAR to acquire 3D point cloud data to minimize the cost compared to commercial 3D LiDAR. The hardware and physical components of 3D point cloud scanner are composed of three major components, the 2D LiDAR device, the tilting mechanism which include the fabricated holder for mechanical tilting and the motor for the rotation movement. In Figure 3.2, the 3D point cloud scanner is placed at the top of the flour bin.

3.1.1 Modeling of Flour Bin

The researcher will model and create a different shapes of the flour bin (e.g. Cylinder, Cube). These different shapes of flour bin will be small-scale and large-scale sizes for testing purposes of the system.

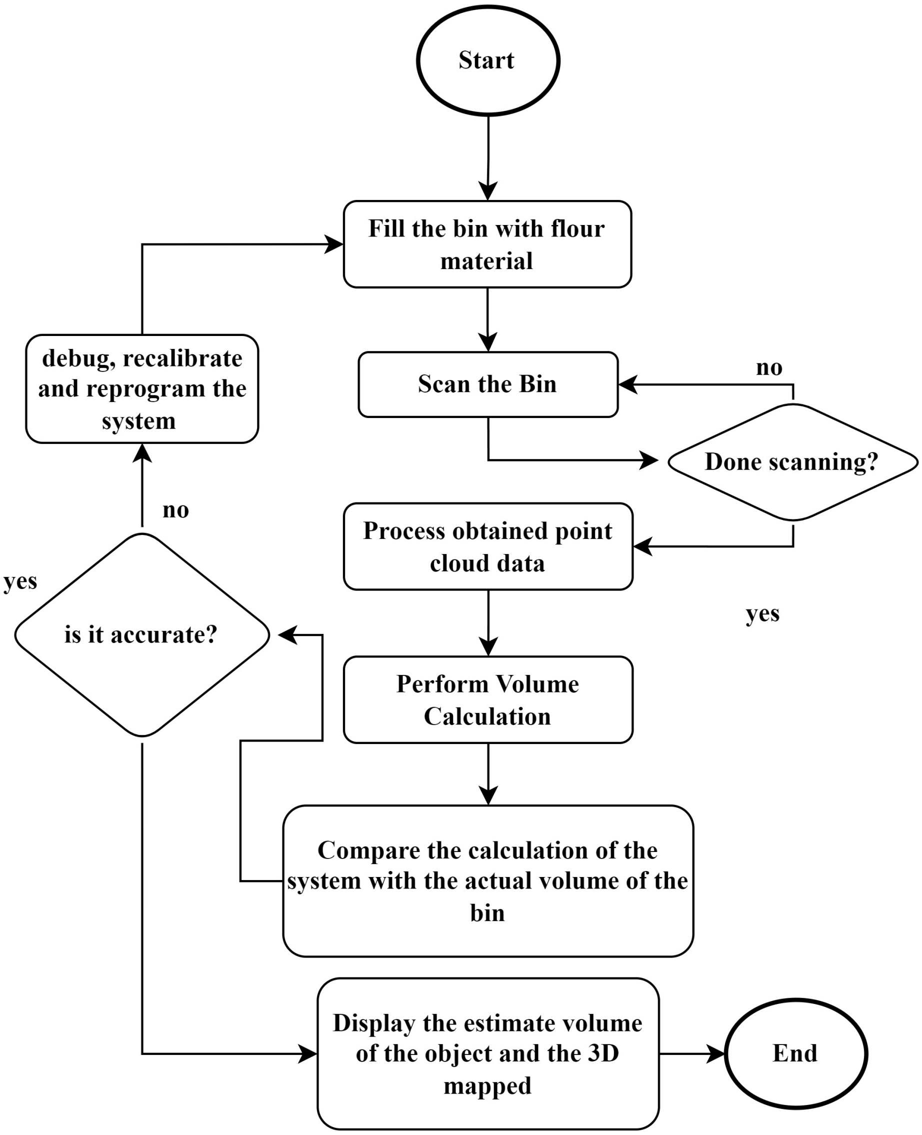

Figure 3.1. General Flowchart of the System

3.1.2 Generating of Dust

The study involves scanning of the bin with the presence of dust, therefore, the researcher will consider to use a blower or fan for generating dust cloud inside the empty space of the bin and flour will be utilize due to its fine-texture.

3.1.3 Data Gathering

For the data gathering of the raw point cloud, all the major hardware of the system will be assemble and integrate as shown in Figure 3.2. The scanned data from the 2D LiDAR sensor will be received by small computer which is Raspberry Pi for the processing of the raw data. This small computer is connected to the internet in order to control remotely by the personal laptop. Different scanning procedure will be performed to gather point cloud data.

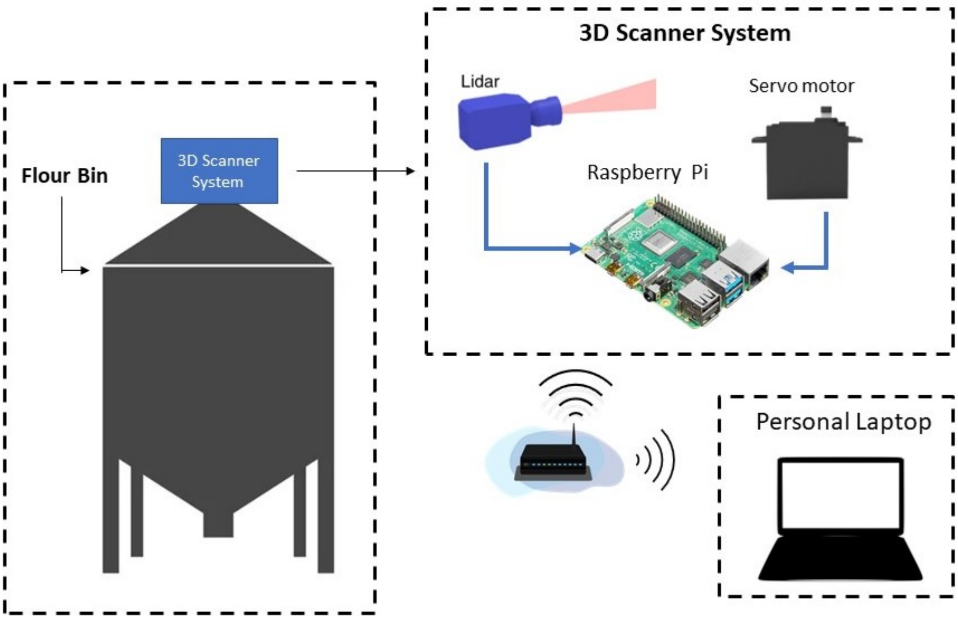

Figure 3.2. System Hardware Block Diagram

3.2 3D Point Cloud Processing

The Raspberry Pi will receive the scanned raw data coming from the 3D point cloud scanner. This data will be processed in different stages to produced desired output, such as point cloud pre-processing (formatting, converting, clustering, and cleansing) and post-processing (e.g., 3D mapping and volume measurement). Various platforms and frameworks nowadays are available to ease the handling of these massive raw data, thus, formatting the data to a desired platform must be perform. Typically, the value of raw data coming from the LiDAR sensor is not directly a point cloud data but rather a value of the distance between the sensor and the reflected nearest object in a particular direction, therefore, the data is converted into point cloud which composed of x, y, and z values. The Equation (3.1), (3.2), and (3.3) is conversion of polar coordinates (distance, angle) to cartesian coordinates x, y, and z, respectively, in a 3D coordinate system.

$$x_{point_i} = \sin(i) \times d \tag{3.1}$$

$$y_{point_i} = \cos(\pi) \times \cos(i) \times d \tag{3.2}$$

$$z_{point_i} = -\cos(i) \times \sin(\pi) \times d \tag{3.3}$$

Where:

i = scan angle of the scanner

d = the distance point of the emitted pulse by the LiDAR (meter)

3.2.1 Point Cloud Data Pre-processing

The researcher will create an algorithm for clustering and cleansing of the raw data. The data will be clustered into two parts, the outliers (dust) data and the inliers (target) data. Based on the behaviors and characteristics of dust, the researcher will use the Multi-echo method for outlier clustering because the laser emitted by the LiDAR will penetrate through the dust cloud and will receive multiple return. Another method that the researcher will utilize is the low-intensity method clustering for outliers due to the characteristic of the dust having a lower intensity compared to other objects. The data cleansing will be employed after all the data is being clustered. After of these processes, the researcher will convert the pre-processed point cloud for further analysis.

3.2.2 Volume Estimation

The researcher will create an algorithm for volume estimation of the material inside the flour bin using Delaunay Triangulation which creates a mesh of triangles such that no point is inside the the circumference of any of the triangle. Convex Hull is a subset of Delaunay Triangulation which creates a boundary on the same given points, all the triangles are on the boundary of the point set. The computation of the estimated volume of the material inside the bin is shown in Figure 3.3 and Equation (3.4).

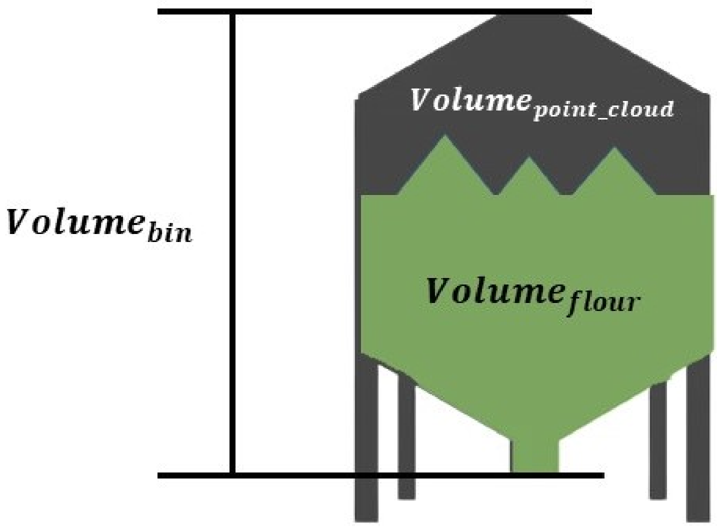

Figure 3.3. Volume of the flour is the difference between the volume of the bin and volume of the point cloud

$$Volume_{flour} = Volume_{bin} - Volume_{point\_cloud} \tag{3.4}$$

3.3 Testing and Evaluation

In this section, the researcher will discuss the different testing and evaluation to test and evaluate accuracy of the system.

3.3.1 Different Testing Procedure

The researcher will conduct different testing and evaluation to observe the accuracy of the system. In the experiment, the researcher will ensure that the prototype flour bin is scanned remotely and without any human intervention. The researcher intends to perform multiple tests to assess the filtering method and validate the precision and effectiveness of the object's volume measurement, and each of the testing will have a multiple trials. The different testing procedure of the system are the following:

1. The system will scan the created different shape of flour bin without materials and dust inside.
2. The researcher will generate a dust in the flour bin but without material inside and scan the bin.
3. The searcher will scan the flour bin with flour material inside with different surface shape but without dust.
4. The researcher will generate dust from the testing structure conducted in testing 3

3.3.2 Evaluation of the System

Based on the conducted different testing mentioned in 3.3.1, the researcher will evaluate the conducted testing based on the volume of scanned data. System in the following evaluation

To evaluate the testing 1, the researcher will measure the accuracy of the system by comparing the estimated volume of the system with the actual volume of the different shape of the bin, calculate the error percentage for each trial and assess the over all precision of the system. Table 3.1 shows the sample comparison of the testing.

Table 3.1. Testing 1

Flour bin Shape	Actual Volume (mm^3)	Scanned Volume (mm^3)	Error (%)
Trial 1			
Cube	-	-	-
Cylinder	-	-	-
Trial 2			
Cube	-	-	-
Cylinder	-	-	-

Testing 2 will be evaluated from the testing 1 based on the number of point cloud acquired of both testing, and compare it. Basically, the testing 2 will acquired more point cloud compared to testing 1 due to multi-echo or multiple returning from the dust and the flour bin.

In testing 3 and 4, the researcher will place flour materials inside the bin with different surface shape and perform volume estimation. After the volume estimation, the researcher will generate dust, scan the bin, perform volume estimation and compare it to the result of the testing 3. The sample result of testing 3 and 4 is shown in table

Table 3.2. Testing 3 and 4

Flour bin Shape	Scanned Volume (without dust)	Scanned Volume (with dust)	Error (%)
Surface Shape 1			
Cube	-	-	-
Cylinder	-	-	-
Surface Shape 2			
Cube	-	-	-
Cylinder	-	-	-

CHAPTER IV

RESULT AND DISCUSSION

BIBLIOGRAPHY

Afzalaghaeinaeini, A., Seo, J., Lee, D., and Lee, H. (2021). Design of a lior-based de-dust filter for lidar sensors in off-road vehicles. *Engineering Proceedings*, 10(1).

Auat Cheein, F. A., Guivant, J., Sanz, R., Escolà, A., Yandún, F., Torres-Torriti, M., and Rosell-Polo, J. R. (2015). Real-time approaches for characterization of fully and partially scanned canopies in groves. *Computers and Electronics in Agriculture*, 118:361–371.

Bewley, A., Shekhar, R., Leonard, S., Upcroft, B., and Lever, P. (2011). Real-time volume estimation of a dragline payload. In *2011 IEEE International Conference on Robotics and Automation*, pages 1571–1576.

Bi, S., Yuan, C., Liu, C., Cheng, J., Wang, W., and Cai, Y. (2021). A survey of low-cost 3d laser scanning technology. *Applied Sciences*, 11(9).

Bucklin, R., Thompson, S., Montross, M., and Abdel-Hadi, A. (2019). Chapter 9 - grain storage systems design. In Kutz, M., editor, *Handbook of Farm, Dairy and Food Machinery Engineering (Third Edition)*, pages 175–223. Academic Press, third edition edition.

Bulut, S., Giese, T. G., Wende, M., and Anderl, R. (2020). The paperless factory: From document driven factories to model driven factories. In *2020 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE)*, pages 725–730.

Chang, W.-C., Wu, C.-H., Tsai, Y.-H., and Chiu, W.-Y. (2017). Object volume estimation based on 3d point cloud. In *2017 International Automatic Control Conference (CACS)*, pages 1–5.

Chua, C. K., Wong, C. H., and Yeong, W. Y. (2017). Chapter four - software and data format. In Chua, C. K., Wong, C. H., and Yeong, W. Y., editors, *Standards, Quality Control, and Measurement Sciences in 3D Printing and Additive Manufacturing*, pages 75–94. Academic Press.

Clar, S. E. and Salaan, C. J. O. (2022). Volume estimation using convex hull method for point cloud-based materials inside a silo.

Duff, E. (2000). Automated volume estimation of haul-truck loads.

Duysak, H. and Yigit, E. (2020). Machine learning based quantity measurement method for grain silos. *Measurement*, 152:107279.

Graham, R. L. and Frances Yao, F. (1983). Finding the convex hull of a simple polygon. *Journal of Algorithms*, 4(4):324–331.

Guevara, J., Arevalo-Ramirez, T., Yandun, F., Torres-Torriti, M., and Cheein, F. A. (2020). Point cloud-based estimation of effective payload volume for earthmoving loaders. *Automation in Construction*, 117:103207.

Heinzler, R., Piewak, F., Schindler, P., and Stork, W. (2020). Cnn-based lidar point cloud de-noising in adverse weather. *IEEE Robotics and Automation Letters*, 5(2):2514–2521.

Jaboyedoff, M., Oppikofer, T., Abellán, A., Derron, M.-H., Loye, A., Metzger, R., and Pedrazzini, A. (2012). Use of lidar in landslide investigations: a review. *Natural Hazards*, 61(1):5–28.

Jeong, D., Li, Y., Lee, H. J., Lee, S. M., Yang, J., Park, S., Kim, H., Choi, Y., and Kim, J. (2018). Efficient 3d volume reconstruction from a point cloud using a phase-field method. *Mathematical Problems in Engineering*, 2018:7090186.

Kang, X., Yin, S., and Fen, Y. (2018). 3d reconstruction & assessment framework based on affordable 2d lidar. In *2018 IEEE/ASME International Conference on Advanced Intelligent Mechatronics AIM*, pages 292–297.

Kim, Y. (2002). Convex hull ensemble machine. In *2002 IEEE International Conference on Data Mining, 2002. Proceedings.*, pages 243–249.

Li, Y., Ma, L., Zhong, Z., Liu, F., Cao, D., Li, J., and Chapman, M. A. (2020). Deep learning for lidar point clouds in autonomous driving: A review. *IEEE Transactions on Neural Networks and Learning Systems*, 32:3412–3432.

Liu, Y. and Zheng, Y. (2021). Accurate volume calculation driven by delaunay triangulation for coal measurement. *Scientific Programming*, 2021:6613264.

Maus, A. (1984). Delaunay triangulation and the convex hull ofn points in expected linear time. *BIT Numerical Mathematics*, 24(2):151–163.

Ocando, M. G., Certad, N., Alvarado, S., and Terrones, Á. (2017). Autonomous 2d slam and 3d mapping of an environment using a single 2d lidar and ros. In *2017 Latin American Robotics Symposium (LARS) and 2017 Brazilian Symposium on Robotics (SBR)*, pages 1–6.

Park, J.-I., Park, J., and Kim, K.-S. (2020). Fast and accurate desnowing algorithm for lidar point clouds. *IEEE Access*, 8:160202–160212.

Putman, E. B. and Popescu, S. C. (2018). Automated estimation of standing dead tree volume using voxelized terrestrial lidar data. *IEEE Transactions on Geoscience and Remote Sensing*, 56(11):6484–6503.

Raj, T., Hashim, F., Huddin, A., Ibrahim, M. F., and Hussain, A. (2020). A survey on lidar scanning mechanisms. *Electronics*, 9:741.

Rakotosaona, M.-J., La Barbera, V., Guerrero, P., Mitra, N. J., and Ovsjanikov, M. (2020). Pointcleannet: Learning to denoise and remove outliers from dense point clouds. *Computer Graphics Forum*, 39(1):185–203.

Ramiya, A. M., Nidamanuri, R. R., and Krishnan, R. (2017). Segmentation based building detection approach from lidar point cloud. *The Egyptian Journal of Remote Sensing and Space Science*, 20(1):71–77.

Rhee, J. H., Kim, S. I., Lee, K. M., Kim, M. K., and Lim, Y. M. (2021). Optimization of position and number of hotspot detectors using artificial neural network and genetic algorithm to estimate material levels inside a silo. *Sensors*, 21(13).

Rusu, R. B. and Cousins, S. (2011). 3d is here: Point cloud library (pcl). In *2011 IEEE International Conference on Robotics and Automation*, pages 1–4.

Sarker, V. K., Qingqing, L., and Westerlund, T. (2020). 3d perception with low-cost 2d lidar and edge computing for enhanced obstacle detection. In *2020 IEEE Conference on Industrial Cyberphysical Systems (ICPS)*, volume 1, pages 49–54.

Shamsudin, A. (2016). Fog removal using laser beam penetration, laser intensity, and geometrical features for 3d measurements in fog-filled room. *Advanced Robotics*, 30.

Stanislas, L., Nubert, J., Dugas, D., Nitsch, J., Sünderhauf, N., Siegwart, R., Cadena, C., and Peynot, T. (2021). Airborne particle classification in lidar point clouds using deep learning. In Ishigami, G. and Yoshida, K., editors, *Field and Service Robotics*, pages 395–410, Singapore. Springer Singapore.

Stanislas, L., Suenderhauf, N., and Peynot, T. (2018). Lidar-based detection of airborne particles for robust robot perception. In Woodhead, I., editor, *Proceedings of the Australasian Conference on Robotics and Automation (ACRA) 2018*, Australasian Conference on Robotics and Automation, ACRA, pages 1–8. Australian Robotics and Automation Association (ARAA), Australia.

Stojanovic, V. (2023). Point cloud analytics: Proposed future work. *Proceedings of the HPI Research School on Service-oriented Systems Engineering 2020 Fall Retreat*, page 137.

Turner, A., Jackson, J., Koeninger, N., Mcneill, S., Montross, M., Casada, J., Boac, R., Bhadra, R., Maghirang, S., and Thompson (2017). Stored grain volume measurementusing a low density point cloud. *Applied Engineering in Agriculture*, 33:105–112.

Turner, A., Jackson, J., Koeninger, N., Mcneill, S., Montross, M., Casada, M., Boac, J., Bhadra, R., Maghirang, R., and Thompson, S. (2016). Error analysis of stored grain inventory determination. *Transactions of the ASABE (American Society of Agricultural and Biological Engineers)*, 59:1061–1072.

Vogt, M. and Gerding, M. (2017). Silo and tank vision: Applicaltions, challenges, and technical solutions for radar measurement of liquids and bulk solids in tanks and silos. *IEEE Microwave Magazine*, 18(6):38–51.

Wang, Q. and Kim, M.-K. (2019). Applications of 3d point cloud data in the construction industry: A fifteen-year review from 2004 to 2018. *Advanced Engineering Informatics*, 39:306–319.

Wang, Q., Tan, Y., and Mei, Z. (2020). Computational methods of acquisition and processing of 3d point cloud data for construction applications. *Archives of Computational Methods in Engineering*, 27(2):479–499.

Williams, G. and Rosentrater, K. (2007). Design considerations for the construction and operation of flour milling facilities. part i: Planning, structural, and life safety considerations.

Yegorova, S. V., Slavyanskiy, A. A., Postnikova, T. A., Pereboev, A. V., Mazanova, G. V., and Murzakov, M. G. (2021). Improving the technology of post-harvest processing and storage of grain raw materials at the enterprises of the grain processing industry. *IOP Conference Series: Earth and Environmental Science*, 640(2):022040.

Yigit, E., İsiker, H., Toktas, A., and Tjuatja, S. (2015). Cs-based radar measurement of silos level. In *2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, pages 3746–3749.

Zhu, R., Ma, S., and Xu, D. (2020). Guided filter simplification method for noisy point cloud data. In *2020 Chinese Automation Congress (CAC)*, pages 6951–6955.