Design of obstacle detection method for autonomous driving in agricultural environments

Sung-Woo Byun[1], Donghee Noh[2], Hea-Min Lee[2]
SMEs Innovation Support Center[1], IT Application Research Center[2]
Korea Electronics Technology Institute (KETI)
Jeonju, Korea
swbyun@keti.re.kr, dhee.noh@keti.re.kr, lee10849@keti.re.kr

***Abstract*— With the rapid development of the internet of things and information and communication technology, several studies into autonomous agricultural vehicles, such as self-driving tractors, drones, and seed-planting robots, have been undertaken. Autonomous farming systems have the potential to produce more crops with less impact on the environment and less effort, and self-driving agricultural vehicles are among the innovative technologies that could be key to future food supplies. In this study, we design an obstruction detection method based on point clouds, for autonomous driving in an agricultural environment. Pulsed LiDAR technology with a bandwidth of 1,550nm is adopted and the LiDAR sensor with an FoV of 90 degrees is utilized. We design a deep learning model to detect property information for structured or unstructured obstructions.

Keywords— Obstacle detection; Autonomous driving; Autonomous agricultural vehicles; Point cloud segmentation

I. Introduction

Many countries have faced problems with food production, due to a decrease in the number of farmers, population aging, and climate change. As reported in [1], in Korea, the population of farmers is expected to decrease by 16.7% between 2015 and 2024, and It is predicted that the proportion of farmers aged 65 or older will reach 43.8% of the total population of agricultural workers by 2024. Demand for the automation and mechanization of agriculture to improve agricultural production has therefore been increasing. With the rapid development of the internet of things and information and communication technology, several studies into autonomous agricultural vehicles, such as self-driving tractors, drones, and seed-planting robots, have been undertaken. Autonomous farming systems have the potential to produce more crops with less impact on the environment and less effort, and self-driving agricultural vehicles are among the innovative technologies that could be key to future food supplies. Globally, major agricultural machinery manufacturers have developed autonomous driving technology. John Deere released an autonomous tractor with an auto tractor controller which can be adapted to other tractors as plug and play kits, and which can recognize obstacles using laser scanners [2]. Case IH proposed an autonomous tractor system [3], which could detect obstacles using a camera and sensors, and could be remotely operated using a tablet. New Holland developed “NHDrive” which can detect obstacles using a combination of light detection and ranging (LiDAR) and cameras [4]. Yammar released the “Yanmar Robot Tractor”, a self-driving robot tractor, with a self-driving system which uses a real-time kinematic (RTK) module and an Inertial Measurement Unit [5]. If autonomous driving agricultural vehicles suitable for agricultural environments are developed, it is expected that the utilization of this technology in agriculture will increase.

Since an autonomous driving agricultural vehicle needs to control its speed, steering, velocity, and position, as well as detecting crops, fruit trees, and obstructions, it should be equipped with sensors such as cameras or LiDAR. The use of existing LiDAR sensors in an agricultural environment has problems, such as difficulties dealing with shadowed areas and a low vertical field of view (FoV) (30 degrees) which does not detect all the crops' environment. Poor conditions, such as sprinkler spray, snow, rain, and dust, are common. In order to solve these problems in an agricultural environment, the use of a LiDAR sensor with a wavelength of 1550nm is valuable, as reflection is less likely to occur due to moisture in the air. It is also necessary to increase the vertical FoV to 90 degrees.

In this study, we designed an obstruction detection method based on point clouds, for autonomous driving in an agricultural environment. Pulsed LiDAR technology with a bandwidth of 1,550nm was adopted and the LiDAR sensor with an FoV of 90 degrees was utilized. We designed a deep learning model to detect property information for structured or unstructured obstructions—distance, height, depth, and speed—from point cloud data from the LiDAR sensor.

The remainder of this paper is organized as follows: Section 2 presents the related works on autonomous driving control methods. Sections 3 explains an obstacle detection scheme for autonomous driving in agricultural environment Section 4 concludes this work.

II. Related works

A. Autonomous driving control method

This section presents the proposed autonomous driving method for the agricultural vehicle with a working machine and a chassis attached to body, such as weeding vehicle and speed sprayer. There are two main parts of the autonomous driving control method: 1) Global Navigation Satellite System

(GNSS)-RTK sensor integrated positioning algorithm, which calculate the navigational information; and 2) Path tracking control algorithm, which predicts the desired vehicle path based on waypoints and the vehicle position [6]. To guarantee stability and accuracy of autonomous driving and continuity of navigational information, the integration of GNSS-RTK and a positioning algorithm was implemented based on extended Kalman filter [7, 8]. To implement autonomous driving method along the desired vehicle path based on current navigational information and waypoints, the path tracking control algorithm calculates control parameters including right and left track velocities. The algorithm consists of four parts: computing the control parameters, switching the waypoint, checking the quality of navigational data, and searching the target point.

B. Point Cloud Segmentation

Point-wise classification or sematic segmentation based on point clouds is a well-known research topic [9]. Availability of largescale datasets, such as Semantic 3D [10], S3DIS [11], and SemanticKITTI [12], made it possible to investigate end-to-end pipelines. Recently, thanks to the emergence of LiDAR-centric datasets [13], 3D object detectors [14], multi object tracking based on LiDAR became popular. Weng et al. [15] proposed simple methods based on constant-velocity motion models and linear assignment which can perform well when 3D object detection methods are localized reliably. Aygun er al. [16] demonstrated 3D object detection in the spatial domain, which localized possible object instance centers within a 4D volume and associated points to estimated centers in a bottom-up manner, while a semantic branch assigns semantic classes to points.

III. Obstacle detection for autonomous driving

A. Pulsed LiDAR device design

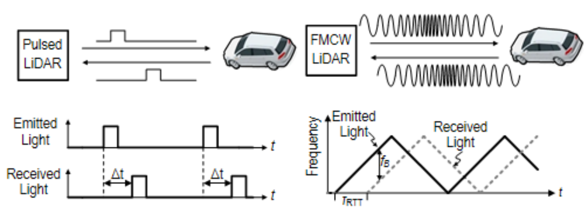

Fig. 1. Comparison of pulsed LiDAR and FMCW LiDAR methods.

Camera sensors have been used to recognize geographic features or crops, using image sequences. However, camera sensors can have low accuracy due to the effects of weather and environment, and additional processing methods are needed to detect distance or depth. LiDAR sensors can be used for multi-object detection, and are robust to weather conditions such as high or low intensity illumination. With the 900 nm wavelength of laser light used in existing LiDAR sensors, the signal-to-noise ratio is high, due to the scattering and reflection of light under poor environmental conditions. To solve these problems, it is necessary to use laser light with a 1,550nm wavelength. We therefore used an avalanche photo diode based on indium gallium arsenide instead of a single photon avalanche diode based on silicon.

There are two main methods of light irradiation: 1) the Pulse 3D method, which transmits and receives only a single pulse intermittently, and calculates the time distance between the transmitted and received pulses; and 2) Frequency Modulated Continuous Wave (FMCW) which generates a continuous waveform, and calculates the distance from the frequency difference between the transmitted and received waveforms. Figure 1 shows examples of Pulse 3D and FMCW LiDAR. Since existing FMCW methods transmit and receive light continuously, increasing laser energy can lead to eye safety problems. To solve the eye safety problem, when detecting objects, we used the Pulse 3D method, which involves radiating the light for a very short period of time. We designed a LiDAR device using the PWM Pulse method in preliminary experiments, as shown in Figure 2.

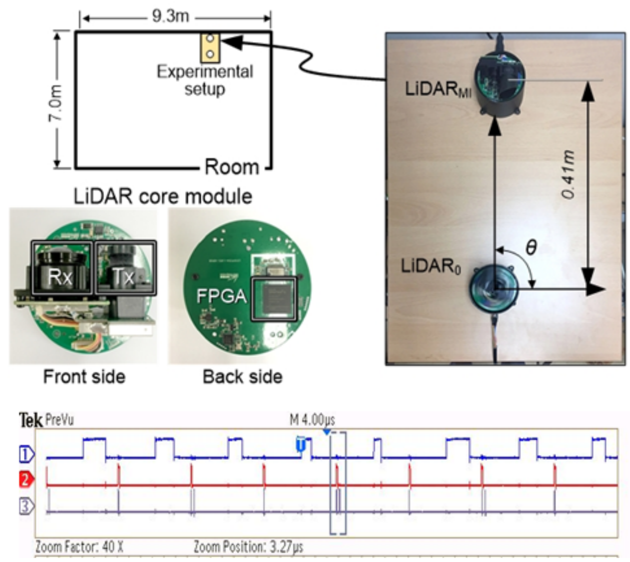

Fig. 2. Pilot study: LiDAR with PWM Pulse method.

B. Obstruction detection using a point cloud

We designed an obstruction detection method based on point clouds obtained from the LiDAR system described in Section 3.1. Figure 3 shows an overview of the obstruction detection method. We obtained data from several consecutive LiDAR scans, and formed 4D point clouds. We identified the most likely instance centers using a neural network model, and assigned semantic classes to points. As well as the most likely object centers in a 4D point cloud, we also needed variance predictions for each point, to evaluate the probability scores during clustering, and a posterior over all semantic classes. To calculate probabilities and a posterior for all semantic classes, we needed to predict the variance for every point. We estimated these quantities utilizing an encoder-decoder network which directly takes a 4D point cloud. The encoder uses the KPConv backbone [17], which is based on deformable point convolutions. The decoder uses consecutive point convolutions to predict point-wise feature embeddings. We added an object, point variance, and semantic decoders, and used cross-entropy loss to train the network.

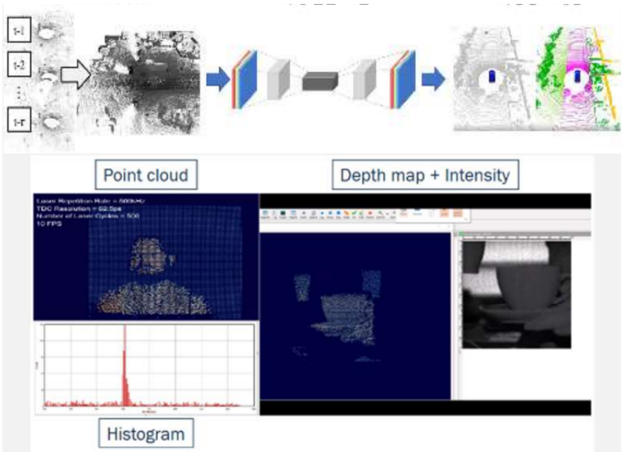

Fig. 3. Overview of the obstruction detection method

IV. Conclusions

In this study, we designed an obstruction detection method based on point clouds, for autonomous driving in an agricultural environment. Pulsed LiDAR technology with a bandwidth of 1,550nm was adopted and the LiDAR sensor with an FoV of 90 degrees was utilized. We designed a deep learning model to detect property information for structured or unstructured obstructions.

In order to accurately learn deep running-based models, a considerable amount of data is required. Therefore, it is necessary to build high-quality datasets in order to improve performance. In future works, we will build 4D point cloud datasets in agricultural environment, considering poor environmental conditions. Furthermore, we will compare reliability and accuracy with previous studies to investigate the performance of the proposed method.

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