Industrial Internet of Things (IoT) and 3D Reconstruction Empowered Smart Agriculture System

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***Abstract*—Smart agriculture is a new agricultural production mode and is considered a potential solution for food supply issues under current limited land space conditions. The application of the Internet of Things (IoT) in smart agriculture can effectively increase food production with relatively low labor costs by deploying various wireless communication sensors in the field to collect plant information during the agricultural process. This paper developed an extendable IoT based sensor system for smart agriculture applications. The proposed sensing system can acquire real-time plant information through its plant environment and plant phenotyping monitoring process. The plant environment monitoring process can collect real-time plant environmental data through multiple wireless environment measuring sensors. At the same time, the plant phenotyping monitoring process can achieve plant height monitoring with the root-mean-square error (RMSE) of 0.051 m and the mean absolute error (MAE) of 0.049 m through remote RGB-D (red, green, blue plus depth data) cameras and 3D reconstruction method. This study shows that the proposed system can provide valuable real-time plant information for farmers' decision-making.**

***Index Terms*—smart agriculture; crop monitoring; IoT; 3D reconstruction.**

I. Introduction

Agriculture is an essential part of the development of human civilization since humans need food to maintain their daily life [1]. Besides, agriculture plays an important role in the economy, which is a crucial part of national development [2, 3]. However, the rapid-increasing population, the unexpected outburst of the pandemic, and war have severely affected the food production and caused global food shortage [2]. The recent crisis demonstrates that new agriculture technologies must be developed to satisfy the food supply for both current and future generations. It means new methods need to be applied in agriculture to increase food production and solve food supply issues along with limited land/field conditions. One potential method to overcome these food supply problems [4–10] to employ smart agriculture with advanced sensor technologies [11, 12].

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Smart agriculture is a new agricultural production mode. It combines agriculture with advanced technologies, including computer vision, the IoT, big data, cloud computing, Artificial Intelligence (AI), etc. Currently, smart agriculture is the common target of agricultural development in worldwide [13, 14]. It is an advanced technology to improve crop yields, and the IoT is one of the main components [13]. The application of IoT in agriculture can effectively increase food production with relatively low labor cost by deploying various low-power wireless communication sensors in the field to collect plant information during the agricultural process [3, 15]. The potential financial benefit of IoT agriculture system is considerable [16].

This paper developed an extendable IoT based sensing system for smart agriculture applications. The system can measure real-time plant environment and plant phenotyping data through various sensors. The measured data will be uploaded to the cloud and can be used for further data analysis to help farmers' decision-making process for harvesting. This work makes the following contributions:

- This study developed an integrated crop and environment monitoring systems for real-time information acquisition. Compared with other monitoring system, this system can acquire crop and environment information at the same time and upload data to cloud for further data analysis.
- The proposed system is an extendable system. Different type of sensors can be easily added or replaced base on the agriculture information requirement.
- The proposed plant phenotyping monitoring process implemented a universal 3D reconstruction process for plant RGB and depth image processing. This process will not limited to the specific hardware. Any type of sensor that has the ability to capture RGB and depth image can easily apply this process.

The paper is organized as follows: Section II states the related works regarding the paper topic. Section III introduces the overview of the whole system and its two monitoring processes. Section IV presents the experiment setup and two

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monitoring process results. Section V summarizes the paper and states the future works.

II. Related works

The current IoT applications for smart agriculture can be classified into seven parts: smart monitoring, smart water management, agrochemicals applications, disease management, smart harvesting, supply chain management, and smart agricultural practices [17]. The IoT-based smart monitoring system aims to improve agricultural products' quantity and quality and has been an essential aspect of smart agriculture. In the plantation field, the vital parts of smart monitoring are crop monitoring and environment monitoring [18]. Various IoT-based sensing systems have been used in crop monitoring and environmental monitoring. In a crop monitoring study, Zhou et al. [19] developed a low-cost IoT based plant phenotyping system. This plant phenotyping system can perform continuous crop monitoring with a high-resolution camera and WiFi-based communication system. The study in [20] proposed an image sensor-based IoT crop monitoring system, which can capture high-resolution plant images in the field and upload all the images to the cloud by the cellular connection for further analysis. Daskalakis et al. [21] proposed a low-cost and low-power smart monitoring system that can measure leaf temperature and leaf water stress. Besides, the technique applied solar energy as its power source. For environment monitoring studies, Mendez et al. [22] developed a Wi-Fi-based smart wireless sensor network for various agricultural environment parameters like temperature and humidity. Vani and Rao [23] proposed an IoT and cloud computing-based sensing system for soil moisture measurement and monitoring by a low-cost soil moisture sensor. The study [24] proposed cost effective IoT-based sensing system for various environmental parameters monitoring. The measured parameters include temperature, relative humidity, and soil moisture. The development of integrated crop and environment monitoring systems with cloud technology is increasing. The integrated system can achieve real-time crop monitoring and environment monitoring. All the real-time monitoring data will be uploaded to cloud through suitable communication protocols. The farmers can access these agricultural data and finish the data processing work for further decision making.

III. System overview

The plantation experiment was conducted in 2021 Winter at the greenhouse of The University of British Columbia Okanagan Campus, Kelowna, Canada. A total of 60 potted wheat plants were cultivated. One IoT-based platform was proposed and set up to monitor the growing conditions of the wheat plants. Fig. 1 presents the overview of the proposed method. The system operates in two phases; (1) Plant environment monitoring process (2) Plant phenotyping monitoring process.

The plant environment monitoring process can obtain the real-time wheat environment parameters by various sensors and upload all the data to Microsoft Azure as cloud storage. On the other hand, the plant phenotyping monitoring process can capture wheat's RGB and depth information and extract plant height information through 3D reconstruction. The detailed information about two processes is presented in the following Section III-A and Section III-B.

A. Plant environment monitoring process

The plant environment monitoring process was constructed based on Libelium Smart Agriculture IoT Vertical Kit. Libelium can work as a wireless plant sensing network to monitor the greenhouse wheat environmental data. The proposed system uses multiple wireless sensors to monitor environmental parameters and transfers data to the IoT gateway for storage.

The proposed plant environment monitoring process contains Meshlium and Waspmote Plug & Sense (with plug-in sensors).

- Meshlium (shown in Fig. 2) is an IoT gateway that contains up to 4 different radio interfaces: WiFi, 4G/3G/GPRS/GSM and 2 XBee/RF radios. Besides, Meshlium can include Bluetooth, BLE, and WiFi for scanning applications.
- Waspmote Plug & Sense (shown in Fig. 2) can serve as a sensor platform for multiple sensors to measure, process, and transfer plant environment data to Meshlium.

In the plantation experiment, Programmed Waspmote Plug & Sense obtains the plant environment parameters (temperature, humidity, pressure and soil temperature) through plug-in sensors. Besides, programmed Waspmote Plug & Sense can set up measurement time intervals and send the data to Meshlium through Xbee 900MHz communication protocol for data storage. After receiving the data from Waspmote Plug & Sense, Meshlium can save the data in a local database and upload the data to Microsoft Azure through ethernet. Since one Meshlium can link to multiple Waspmote, this process can measure extensive area plant environment data by setup multiple Waspmote in the fields. In this experiment, two Waspmote were used and linked to Meshlium.

B. Plant phenotyping monitoring process

The plant phenotyping monitoring process was constructed based on Raspberry Pi 4 and an RGB-D camera. In the plantation experiment, the greenhouse set up a 10x10 Ft heavy duty photo backdrop stand where the Raspberry Pi 4 and two RGB-D cameras were mounted for taking RGB and corresponding depth images of wheat plants, which are used to do the 3-D reconstruction to obtain the plant height information.

Raspberry Pi serves as a portable computer connected to RGB-D cameras and applied cameras to take the wheat plant's RGB and corresponding depth image in the plant phenotyping monitoring process. After taking the wheat plants image, Raspberry Pi automatically uploads the saved RGB and depth images to Microsoft Azure for later data analysis. A laptop remotely monitors the current output of cameras connected to Raspberry Pi through VNC/SSH and sends the image saving instruction to Raspberry Pi. The plantation experiment shows that one laptop can be used to

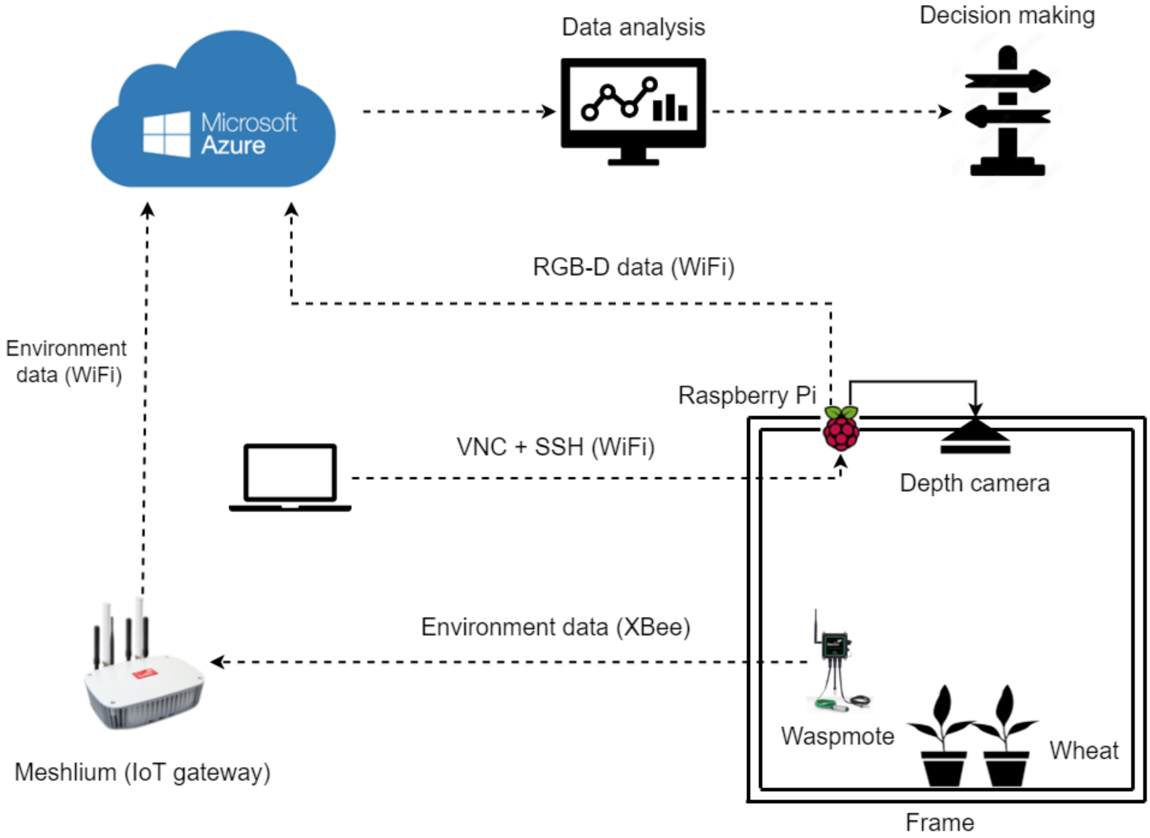


Fig. 1. Proposed sensing system for smart agriculture application.

control multiple Raspberry Pi and corresponding cameras. Therefore, this plant phenotyping monitoring process can work for numerous fields of plant phenotyping data.

After uploading the plant images to Microsoft Azure, the user can download the images and obtain the plant phenotyping data through the 3D reconstruction process shown in Fig. 3. First of all, Open3-D library [25] will be applied to process the plant RGB image and corresponding depth image (shown in Fig. 4) and convert them to a raw point cloud map. Then, the raw point cloud map will be processed through MATLAB point cloud processing functions and generate the visualized 3D reconstruction result. Fig. 5 shows visualization result. In this result, clicking any cloud points will return the corresponding coordinates information (X, Y, Z), which can be applied to estimate crucial plant phenotyping information: plant height. The plant height can be estimated by subtracting the Z-value of the vegetation points from the height of the depth camera and the height of the pot. For instance, H is plant height data, Z_3 is the Z-value of wheat vegetation points, Z_1 is the Z-value of the camera to the ground (a mark was used as a reference point of the ground), and Z_2 is the height of the plant pot (manually measured).

$$H = Z_1 - Z_2 - Z_3 \tag{1}$$

IV. Experiment and Result Analysis

A. Experiment setup

The proposed system was evaluated at the greenhouse of The University of British Columbia Okanagan Campus. The plant environment monitoring process includes one Meshlium and two Waspmote Plug & Sense with various environment sensors (Temperature, Humidity and Pressure probe/Soil temperature (Pt-1000) probe). Two coded Waspmote Plug & Sense were placed in two plant pots to measure the environmental data and send data to Meshlium by their Xbee modules. The plant phenotyping monitoring process includes Raspberry Pi 4B 8 GB version, one ASUS ROG laptop, one Intel RealSense Depth Camera D455, one OpenCV AI Kit: OAK—D camera, and one 10x10 Ft heavy duty photo backdrop stand. Two depth cameras and Raspberry Pi are mounted on the shelf at 1.88 m height above the pot to capture the images of wheat. Besides, a laser tape measure was used to get the ground truth plant height data.

B. Results of Plant environment monitoring process

In the plant environment monitoring process, Waspmote Plug & Sense successfully obtained the real-time plant environment data and sent these data to Meshlium through Xbee modules. Table I shows the environment data that the Meshlium received.

(a) Meshlium.

(b) Waspmote Plug & Sense.

Fig. 2. Meshlium and Waspmote Plug & Sense.

TABLE I
PLANT ENVIRONMENT DATA

Date	**Node name**	**Soil Temperature (°C)**	**Pressure**	**Humidity**	**Temperature (°C)**
2021-11-24 12:47:24	Waspmote node 1	24.68 °C	97393.13 Pa	87.7 %	24.56 °C
2021-11-24 12:47:24	Waspmote node 2	24.78 °C	97395.64 Pa	88.9 %	24.64 °C
2021-12-08 12:20:46	Waspmote node 1	24.87 °C	97394.89 Pa	87.5 %	24.67 °C
2021-12-08 12:20:46	Waspmote node 2	24.88 °C	97396.53 Pa	88.4 %	24.62 °C
2021-12-22 11:50:43	Waspmote node 1	25.42 °C	97394.70 Pa	87.9 %	25.22 °C
2021-12-22 11:50:43	Waspmote node 2	25.23 °C	97395.98 Pa	88.8 %	25.08 °C

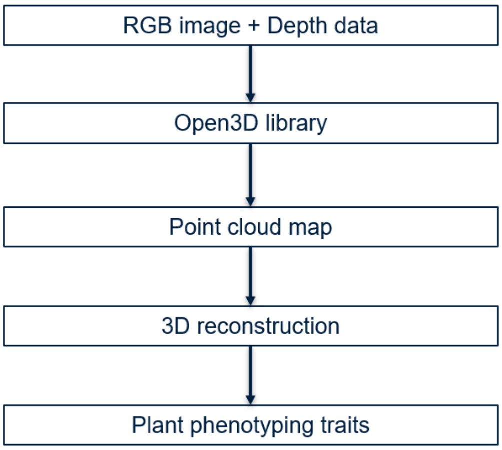
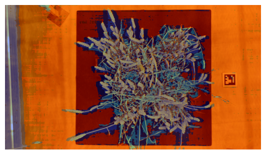


Fig. 3. 3D reconstruction process.

(a) Intel wheat RGB image

(b) Intel wheat depth image

(c) OAK-D wheat RGB image



(d) OAK-D wheat depth image

Fig. 4. Wheat RGB image and depth image.

C. *Results of Plant phenotyping monitoring process*

In plant phenotyping monitoring process, two depth cameras successfully obtain wheat RGB image and corresponding depth image. Raspberry pi saved these images and uploaded them to the cloud for further processing. These saved images were accessed through the cloud and processed by the pro-

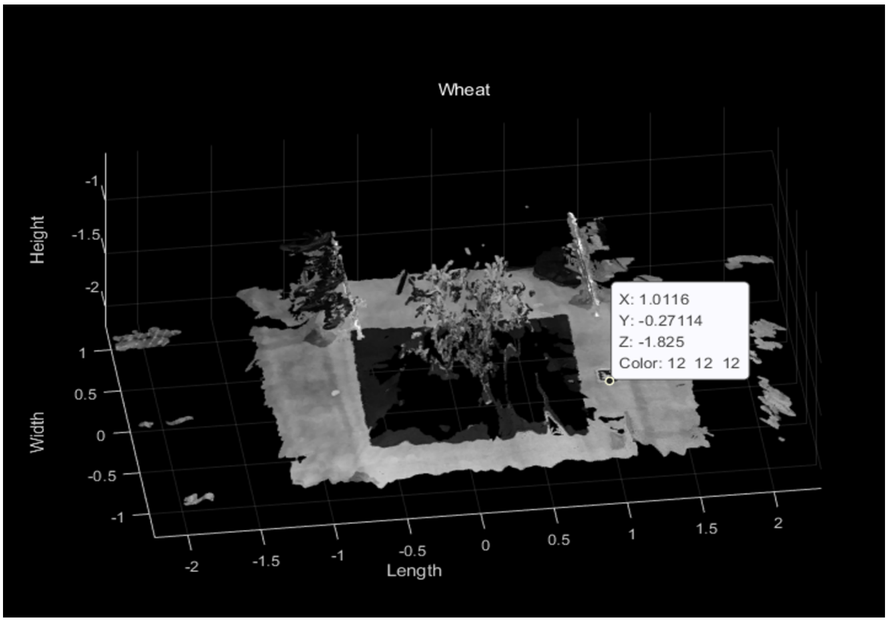


Fig. 5. 3D reconstruction result.

posed 3-D reconstruction method for plant height acquisition. The images were captured in the mature wheat stage. Sensor measurements of plant height were compared with the ground truth of plant height data. Four pots of wheat are considered to be a group to be measured, and the plant height data are the average of four pots measurement values. The results of plant height and corresponding error analysis are showed in Table II.

V. Conclusion

This paper developed an IoT based extendable sensing system for smart agriculture applications. The proposed approach can acquire valuable real-time agricultural plant information through two integrated monitoring processes. Besides, the acquired plant information can be synchronized to the cloud for further data analysis work. The up to date data and analysis result can help agriculture decision making like agricultural environment management and breeding selection. In future work, we seek to implement additional environment sensors (luminosity sensor/soil oxygen sensor) and plant phenotyping sensors (infrared camera/fluorescence sensor) in the current sensing system. Besides, developing a detailed data analysis process for plant growth prediction will also be a future research work.

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TABLE II
PLANT HEIGHT DATA

Wheat group	Ground truth plant height	Intel D455 result	OPENCV OAK-D result
Group 1	0.895 m	0.842 m	0.835 m
Group 2	0.847 m	0.803 m	0.801 m
Group 3	0.815 m	0.772 m	0.771 m
Group 4	0.884 m	0.835 m	0.842 m
Group 5	0.836 m	0.803 m	0.784 m
Group 6	0.867 m	0.806 m	0.798 m
	Root-mean-square error (RMSE)	**0.0479 m**	**0.0531 m**
	Mean absolute error (MAE)	**0.0472 m**	**0.0522 m**

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