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Proposal of a Point Cloud Inter-Day Registration Method for Agricultural UAV Monitoring

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Abstract— **Continuous crop monitoring is essential for inspection of pests, diseases, and the evaluation of crop growth. It requires registering sensor data from the same field over a period of time. Agricultural fields can be effectively monitored by cameras or LiDAR mounted on unmanned aerial vehicles (UAVs). However, due to significant changes in crop growth and soil conditions over different measurement periods, conventional data registration methods often fail to reduce the loss of accuracy.**

In this study, we proposed a point cloud registration method that utilizes static geometric information of crop rows and terrain to align maps from different measurement periods. In our experiments, we first created a map with accurate positional data using LiDAR at the beginning of the season. We then generated maps by Structure from Motion (SfM) 5 days later, when ground information had notably changed due to tractor activity, and the other map 19 days later when crops had grown considerably. The proposed method was applied to register the maps generated in different periods. The result of a demonstration by using precise positional information obtained at the start of the season showed that we were able to align maps taken up to 19 days apart with displacements of no more than 30 cm.

I. INTRODUCTION

In Japan, the agricultural sector faces increasing labor shortages due to an aging society, where 70% of farming workforce compose of elderly people[1].

To address this issue, the adoption of smart farming technologies, particularly in automation, robotics, and communication, is gaining momentum. A crucial aspect of smart farming is continuous monitoring, which allows for the detection of pests and diseases and the evaluation of crop growth over time. This requires repeated measurements of the same field throughout the growing season and accurate alignment of data collected across different periods.

UAVs play a pivotal role in automating agricultural monitoring due to their ability to capture high-resolution data over large areas.However, registering data collected at different times remains challenging. Existing methods for map registration from various periods by establishing Ground Control Points (GCPs) and manually inputting geographic information provide accurate correlating measurement results. Implementation of the GCPs can disrupt agricultural activities such as those involving tractors. Moreover, maintaining GCPs throughout the season presents challenges. Consequently, insufficient GCP setup may result in reduction of alignment precision and inaccurate monitoring of agricultural operations. Therefore, to solve these challenges, an automated alignment technology that does not depend on long-term GCP management is required.

Chen et al. [2] proposed an innovative non-required long-term GCP management method. Their approach involved creating an initial map by manually linking geographic information with GCPs at the start of the season, followed by automatic alignment of images over time. Chen et al.'s method involved retraining the deep learning feature in LoFTR [3] so that the network matched the field. Their study demonstrated that general deep learning features can achieve high-precision registration despite changes in the field. However, they also suggest that accuracy may decline due to variations in crop types, field conditions, crop shapes, sowing densities, and row distance. Therefore, diversity of dataset would address the mentioned variations.

This paper focuses on the static characteristics of crop row centers in a typical agricultural field. We propose a point cloud registration method that extracts the point cloud representing the center of crop rows utilizing color information and point cloud processing. By utilizing our method's intuitive parameters, extraction of crop rows can be easily achieved across various types of fields.

The contributions of this study are as follows:

1) A novel registration method for maps measured at different periods using color information and point cloud information
2) The individual components are well established; however, the method integrates general parameters, such as crop row spacing and angular differences between rows, which are common features of typical farmland. Its effectiveness was demonstrated through alignment experiments conducted on actual farmland.
3) Demonstration of the method's robustness by comparing results from UAV-LiDAR-generated maps with those from Structure from Motion (SfM)-generated maps taken at intervals of up to 19 days.

The structure of this paper is as follows: Section II reviews previous research about inter-day registration of agricultural fields. Section III describes the proposed method. Section IV demonstrates the proposed method's application to the measurement results of a potato field and evaluates its effectiveness. Lastly, Section V presents the conclusions.

II. RELATED WORK

Agricultural robots, including UAVs and UGVs, are valuable tools for boosting productivity and reducing labor in

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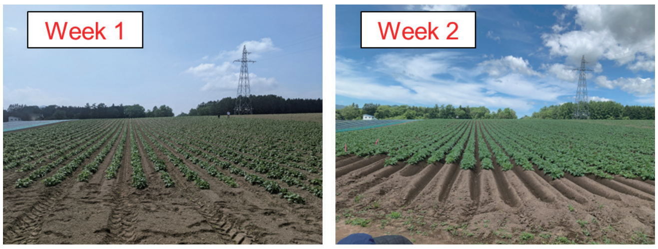

Fig. 1: View of the same area on the field a weeks apart. In addition to vegetation growth, soil conditions also changes significantly over time. In the right image, the soil conditions have changed dramatically with the tractor.

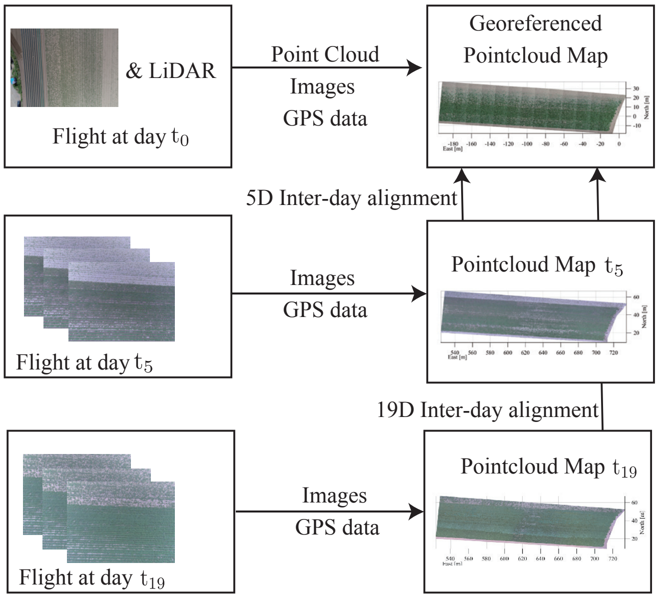

Fig. 2: Inter-day map registration pipeline - The registration process involves performing an intra-day 3D reconstruction for each day. After this, an inter-day registration is implemented

agriculture. Various methods have been proposed to effectively manage the maps and images obtained by these robots throughout the season for matching inter-day images of the fields. Conventional image registration methods typically use local features such as SIFT[4] and ORB[5]. However, the field appearance changes significantly over the week in the agriculture sector, as shown in Fig. 1. The changes are attributed to weather, crop growth, and the uses of tractors and other farming equipment. These strong changes in appearance present a considerable challenge for visual matching methods[6].

In the field of smart farming, two approaches have been considered as a way to address these changes in appearance, which be described in the sections that follow.

A. *Image registration utilizing deep learning features*

The first approach utilized deep learning features such as SuperPoint[7] and LoFTR. Sarlin et al. [8] proposed a state-of-the-art visual localization method that utilizing global descriptors and local features. Their approaches achieved highly precise matching and localization, even though implemented under large-scale and light-varying environments.

In agriculture, Chen et al. [2] proposed a method that refines LoFTR features for improved matching accuracy in deep learning-based techniques. However, a significant drawback of this approach is its time-consuming nature, as it requires additional training for each individual field.

B. *Registration methods utilizing geometric shapes and features of agricultural fields*

The second approach utilized a geometric constraint-applied registration method based on the inherent structure of the field such as crop rows.

Chebrolu et al. [9] utilized crops from rows with regular intervals to assume the missing crops as static feature points for matching. In addition, Kim et al. [10] proposed a matching method that focuses on locations with no elevation changes, such as roads surrounding the field.

These methods have been criticized for their limitations in specific conditions such as numerous crops missing and many roads surrounding the field [2].

Conversely, several studies have utilized not only images but also three-dimensional information. Luca et al. [11] focused on the unique characteristics of the immobile base of crops in a pepper field. They successfully achieved the localization of UGVs and the registration of temporally separate data. The accomplishment was mainly based on the coarse alignment between point cloud registration and image feature matching. However, this method necessitated crop isolation and proximity information.

Currently, there are no existing methods that combine both point cloud and image processing in UAV measurements. This study presents a novel algorithm for inter-day registration-based point cloud processing.

In our study, we implement the concept of integrating both point cloud and image processing approaches. Color information and the RACSAC algorithm [12] were altogether used to extract the crop rows from point cloud maps. Subsequently, the registration of these rows using the ICP algorithm [13] was also achieved.

III. METHOD

This section presents a overall approach for generating 3D maps of a crop field over different periods and accurately aligning them. We describe the inter-day agricultural field's map alignment, achieved by crop row point cloud extraction and row point cloud alignment.

A. *Assumptions and Overview of registration pipeline*

Our method is based on the assumption of an agricultural environment where crops are planted in parallel rows with uniform spacing. The exact locations of the crops are considered unknown. In large-scale fields, tractors are predominantly automated, and the rows of crops are typically parallel and evenly spaced. This assumption is common

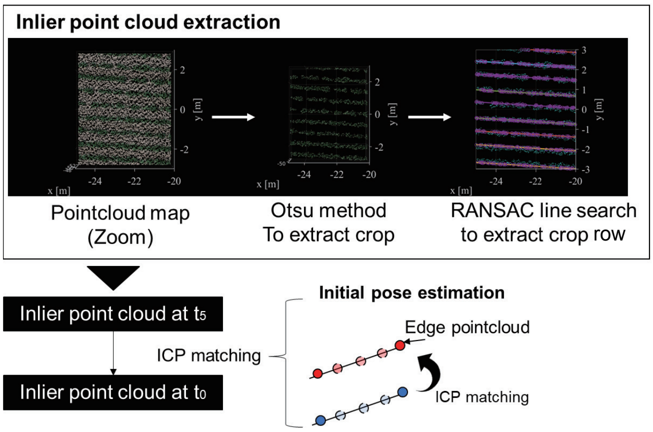

Fig. 3: Inter-day map registration method - the process of extracting point clouds near row centers and registration them through ICP algorithm.

in agricultural practices for crop planting and serves as a reasonable foundation for our proposed method.

Figure 2 illustrates the inter-day map registration pipeline. Initially, the potato field map was accurately georeferenced using laser scanning. Alternatively, photogrammetry software was also able to establish ground control points and link the data to a geographic coordinate system. Subsequently, UAV flights were conducted on various periods. For each date, maps were prepared through SfM-based 3D reconstruction. Each of these maps was aligned without GCPs.

The core of our method is the inter-day registration, as illustrated in Fig. 3. Initially, the point cloud map of the field is utilized to extract only the crop data through two key algorithms: the row extraction algorithm and the row alignment algorithm. Detailed descriptions of each algorithm will be provided in the following sections.

B. Extract crop in the agricultural field

Our approach capitalizes that once crops are planted, they remained stationary from the fixed stem. The crop extraction is explained in the following steps.

1. Compute the Vegetation Mask: The Excess Green minus Red index (ExGR) is defined as

$$\mathrm{ExGR} = \mathrm{ExG} - \mathrm{ExR} \tag{1}$$

where ExG and ExR are given by

$$\mathrm{ExG} = 2g - r - b \tag{2}$$

$$\mathrm{ExR} = 1.4r - g \tag{3}$$

In these equations, r, g, and b represent the normalized color intensities for red, green, and blue, respectively, in the original point cloud. This filter generates a grayscale image [14].

2. Apply Otsu's Method: Otsu's method [15] is used to determine the threshold θ for the ExGR image, enabling the extraction of the point cloud corresponding to the crops [16].

C. Detection of crop rows and extraction of row centers point cloud

To detect the crop rows, the extracted point cloud referring to the crop is normalized to the x-y plane. Then RANSAC performed line detection.

By using the RANSAC algorithm, groups of points are randomly selected to fit with a line. The constructed line is continually refined until the number of inliers reached a predetermined threshold. Assuming that the number of rows are unknown, the RANSAC algorithm is consistently applied to the entire point cloud of crops. The RANSAC algorithm required a specific range for inliers which is set between 0.2 and 0.3 meters in this study. This value can be intuitively adjusted depending on the space between crop rows in the field.

The $L_i(m_i, b_i)$ obtained by the RANSAC algorithm is given by

$$L_i(m_i, b_i) = m_i x - y + b_i = 0 \tag{4}$$

$$\theta_i = \arctan(m_i) \tag{5}$$

All lines are assumed to be parallel to each other. Lines with an angle θ_i deviating more than 0.2 radians from the median angle are excluded from the calculation. Given that the longitudinal direction is about 200 meters, a 0.2 radian deviation would result in a row shift of about 20 meters vertically over 100 meters, leading to an intersection between rows. Therefore, a threshold of 0.2 radians is established.

For the estimated line, the point cloud representing the center of a row is defined as the inlier points within a 5 cm distance to the line. This procedure ensures the extraction of center points and maintains consistency over time.

D. Registration of Crop Center point cloud

First, the crop center point clouds at each time point are extracted based on the previously described method. After the point clouds representing each row's center are successfully extracted in the previous section, the most well-known ICP algorithm is applied to align point clouds acquired at different periods.

The objective function for the ICP algorithm is expressed as following

$$E(T) = \sum_{(\mathbf{a},\mathbf{b}) \in \mathscr{K}} (\mathbf{a} - \mathbf{T}\mathbf{b})^2 \tag{6}$$

where T, a, b, and $\mathscr{K}$ referred to the rigid transformation matrix, fixed point clouds, target point clouds, and the set of corresponding points, respectively. However, the ICP algorithm is sensitive to initial values and prone to converge to a local solution if the source and target point clouds are not sufficiently close to each other. In our method, the initial rigid transformation is applied to align the edge points of the crop rows as the initial estimation. Subsequently, the full-row point clouds are aligned using ICP matching. This approach enables high-precision matching between various sets of data obtained throughout the season.

IV. Experimental evaluation

This section presents the flight experiments conducted for the analysis and validation of the proposed system, and its results.

A. Agricultural data

In this study, we utilized an UAV, DJI's Matrice 300 RTK, to measure a potato field located in Hokkaido of Japan with an area of approximately 40 m × 200 m. The initial measurement was conducted on June 14, when the crop was beginning to sprout. The second measurement was conducted on June 19, when the ground had changed signifi- cantly due to tractor work compared to the first measurement. The third measurement was conducted on July 3, when the crop had grown to near maximum size.

For the initial measurement, serving as a reference for alignment, DJI's Zenmuse L1, a laser scanner, was employed. The Zenmuse L1 is equipped with an RGB camera with a resolution of 5472 [pixel] × 3078 [pixel] , enabling the acquisition of a colorized point cloud. We then utilized DJI Terra to generate point cloud maps for the analysis of the Zenmuse L1 data. The UAV was equipped with a 720 [pixel] × 480 [pixel] RGB camera for the subsequent imaging sessions. The images captured were labeled with GPS data from the UAV. Agisoft's Metashape utilized SfM and to generate colorized point cloud maps.

The point clouds generated by SfM were first verified for map accuracy using GCP alignment. After confirming the accuracy, the initial positions were shifted by several hundred meters to prevent the maps from overlapping before being saved. This adjustment was made to account for cases where the maps lack a geographic coordinate system or have low linkage accuracy.

B. Result of registration inter-day maps

The data collected on June 14, 2024, the first day, was used as a reference. t_N referred to data collection date where N specified the number of passing days after June 14.

Figure 4 and Figure 5 illustrated the registration results at intervals of t_0 to t_5 and t_0 to t_{19} respectively. Both of them showed well parallel and aligned rows of point clouds collected in different periods.

C. Ground reference for evaluation

This section presents the position evaluation by GCPs. For GCPs, five squares with a length of 45 cm were placed on the fields as shown in Fig. 6. The positions of the GCPs were obtained by RTK-GNSS.

D. Evaluation of inter-day matching algorithm

Methods in evaluation composed of the proposed method and two color-based alignment methods as follows:

1) **Proposed Method**: ICP with coordinates of the extracted center of the point clouds.
2) **Colored ICP**: objective function aided with color information. function[17]
3) **Colored GICP**: ICP with objective function aided with color and normalized point cloud information function.

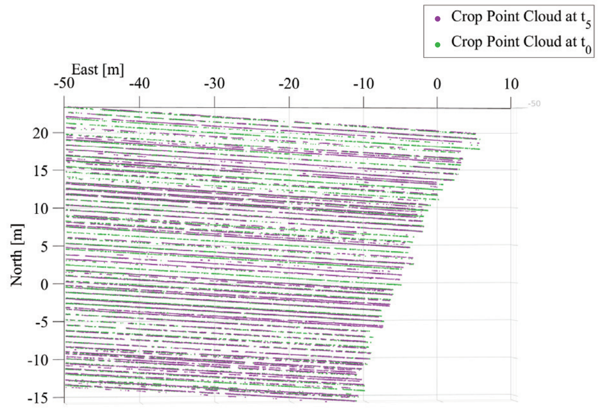

Fig. 4: Result of crop row registration at $t_0 - t_5$: zoom

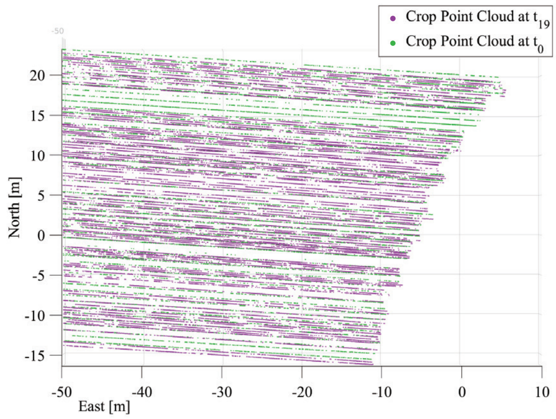

Fig. 5: Result of crop row registration at $t_0 - t_{19}$: zoom

The RMSE of GCP positions for each method is shown in Table I. The proposed method demonstrated significantly higher horizontal accuracy compared to other methods. In cases with a short time interval of 5 days, the vertical accuracy of the proposed method was nearly identical to that of the other methods. However, in terms of horizontal accuracy, it outperformed all others, achieving alignment accuracy within 10 cm. Moreover, even with a longer time interval of 19 days, where the horizontal accuracy of other methods exceeded 2 meters, the proposed method maintained a remarkable accuracy of less than 30 cm.

Since point cloud alignment relies on geometric information, vertical components influenced by terrain tend to align well. However, horizontal components, which are strongly governed by crop positions, are more challenging. By utilizing center coordinates, the proposed method successfully improved the accuracy of these horizontal components.

TABLE I: Evaluation of our registration pipeline. Reported are the horizontal and vertical RMSE of GCP location for aligned models.

	(1) proposed		(2) Colored ICP		(3) Colored GICP	
	horizontal [m]	vertical [m]	horizontal [m]	vertical [m]	horizontal [m]	vertical [m]
t0 - t5	0.0886	0.2526	2.8461	0.2028	0.4445	0.2462
t0 - t19	0.2606	0.2988	2.2812	0.3404	4.0858	0.2946

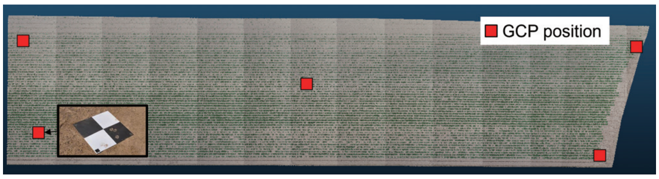

Fig. 6: Positions of GCP in the field

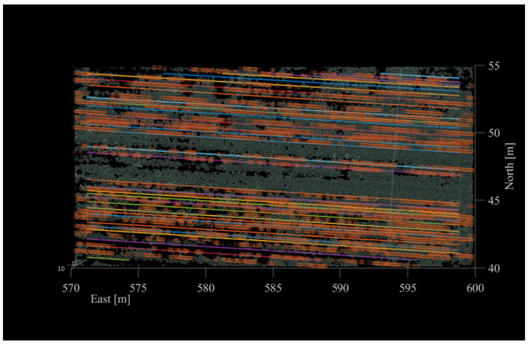

Fig. 7: Example of regions where column extraction failed at t_{19}. Orange indicates the extracted line point cloud, while green shows the original crop point cloud.

E. Discussion

Although the objective function of Colored ICP and Colored GICP cooperated with the shape and color information of the point cloud, the colors of each point cloud do not match perfectly due to varied measuring period. Furthermore, volume of crops increased due to normal growth contributing to horizontal accuracy reduction. The vertical accuracy achieved by the terrain-based registration method is comparable to that of the proposed method.

In Figure 5, gaps present at t_{19} defined extraction failure. The prominent gaps overlaid the original point clouds as shown in Fig. 7. This indicated that the gaps between rows became narrower due to crop growth, which enriched incorrect row detection. Specifically, for crops with a narrow space between rows and those that become indistinguishable from overhead due to growth (e.g., wheat), the proposed method may not function effectively, posing potential issues.

V. CONCLUSIONS

This paper has described the method for UAV-based map registration in which features kept changing over time. This registration issued a significant challenge due to the alignment ambiguity caused by changes in appearance of fields and plants over time. The RANSAC-based central point cloud extraction method utilizing color information and ICP-based registration method were proposed. In this study, the proposed method was evaluated by a long-term dataset of a potato field. The proposed method demonstrated improvement on accuracy compared to our dataset's conventional color-based point cloud alignment methods.

It was found that the proposed method could face difficulties in identifying crop rows due to overlaps caused by crop growth. Additionally, while the ExGR and Otsu methods improved the robustness of the proposed method against illumination changes and crop growth, further validation using datasets with more diverse sunlight conditions is necessary. Therefore, additional experiments are required to enhance the flexibility of the proposed method and enable its application across a wider range of scenarios. As a prospect, we plan to validate the versatility of the proposed method by conducting experiments conducted in various fields. Furthermore, we aim to enhance the accuracy and adaptability of the method by integrating it with alternative strategies independent of crop growth.

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