Detection of Convallaria Keiskei Flower by Combining Convolutional Neural Network and Fuzzy C-means Using Unmanned Aerial Vehicle-based Data

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Abstract

Services and operations have been systematized to realize Society 5.0, and the use of processing technology for images acquired by unmanned aerial vehicles (UAVs) is highly effective in improving productivity. Conversely, the Convallaria keiskei, a plant native to Japan, was once on the verge of extinction. Since then, the management and species identification of Convallaria keiskei have been performed manually. Therefore, automatic species identification and population estimation of Convallaria keiskei using image processing and machine learning can reduce the management costs. In a previous study, we proposed flower number estimation by combining image processing, convolutional neural network, and fuzzy c-means (method A). In this study, we evaluate the method A using UAV data obtained in 2022. To validate the method A, it was compared with the CNN-based detection method (method B). The results show that the method A improved the F-measure by up to six of the seven UAV datasets compared with the method B.

Keywords: Unmanned Aerial Vehicles, Convolutional Neural Network, Fuzzy C-means.

1. Introduction

In recent years, services and operations have been systematized toward the realization of a super-smart society (Society 5.0)[(1)]. In this context, processing technology for images (UAV data) acquired by unmanned aerial vehicles (UAVs) is useful in improving productivity[(2)].

On the other hand, Convallaria keiskei, which grows in Japan, was in danger of extinction for a while. Since then, management and species identification of Convallaria keiskei have been conducted manually[(3)]. Therefore, we believe that the automatic identification of species and population estimation of Convallaria keiskei using image processing and machine learning will enable us to reduce management costs. Recently, various approaches have used UAVs for vegetation management. Gonçalves et al. detected invasive species of Acacia longifolia using UAV data[(4)]. In that study, certain areas were extracted from the data and land cover classification was performed. However, population detection has not been attempted.

In a previous study, we proposed flower number estimation using a convolutional neural network (CNN)[(5)]. However, false positives were observed and the detection accuracy was not always sufficient. Therefore, to reduce false positives, we propose flower number estimation by combining image processing, CNN, and fuzzy c-means (FCM)[(6)]. The method reduced misidentification, as it ignored the regions that appeared similar to the flowering regions. In this study, we evaluate a method using UAV data obtained in 2022. As evaluation indices, precision and F-measure were calculated to evaluate each method.

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2. Study Area and Data Used

2.1 Study Area

Convallaria keiskei blooms annually in the Tohoku and Hokkaido regions of Japan. A typical plant of this species produces approximately 5–10 white flowers and two leaves per colony. In this study, the colonies under observation were located in Biratori-cho, Hokkaido, Japan (Fig. 1). In Biratori-cho, this species was declared to be endangered in 1975. It has since been managed manually and its population has been stably maintained. However, due to the social problem of a dearth of successors in Japan, it is difficult to obtain sufficient personnel to manage vegetation. Therefore, automation of Convallaria keiskei management is essential.

2.2 Data Used

2.2.1 UAV Data

In Biratori-cho, Convallaria keiskei blooms between late May and mid-June. UAV data (seven images, labeled A–G) were acquired on June 2, 2022, using a visible camera onboard Phantom 4 Pro[7]. Fig. 2 shows examples of UAV data.

2.2.2 Dataset

Two types of dataset were extracted from the UAV data taken in the visible range (red, green, and blue). The size of dataset A is 16 × 16 (pixels) × 3 (bands). The size of dataset B is 32 × 32 (pixels) × 3 (bands). Table 1 lists the summary of each dataset. Each training process was repeated 100 times. Examples of each dataset are shown in Fig. 3.

3. Analysis Method

Fig. 4 depicts a flowchart outlining the combined CNN and FCM-based detection method (method A)[6] and the CNN-based detection method (method B)[5].

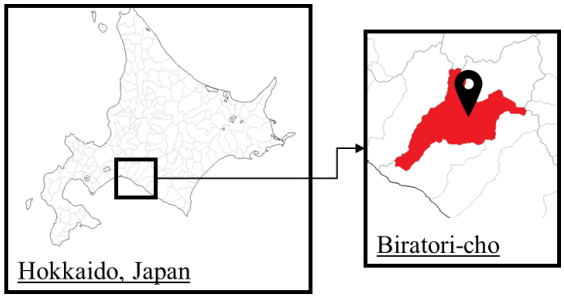


Fig. 1. Study Area.



Fig. 2. Example of UAV Data (image C).

Table 1. Summary of each dataset.

		Training data	Test data
Dataset A	positive	800	200
	negative	800	200
Dataset B	positive	800	200
	negative	800	200

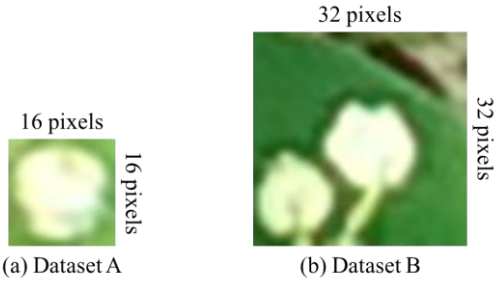


Fig. 3. Dataset.

3.1 Classification via FCM and Mask Processing

Remote sensing (UAV) data contained unclear images. Therefore, the FCM clustering method[8], which included unclear images in the analysis, was used. The images were generated using UAV data, and the merged images were obtained from the dataset A training data. We used the red and blue color information to distinguish between the flower and leaf regions, generated red and blue grayscale images, and converted the red and blue images. The images were converted using Equation (1).

$$DN = \text{Red} * 5 + \text{Blue} \quad (1)$$

Next, each feature image was classified into 12 classes using FCM. The FCM flow diagram is shown in Fig. 5. Here, the

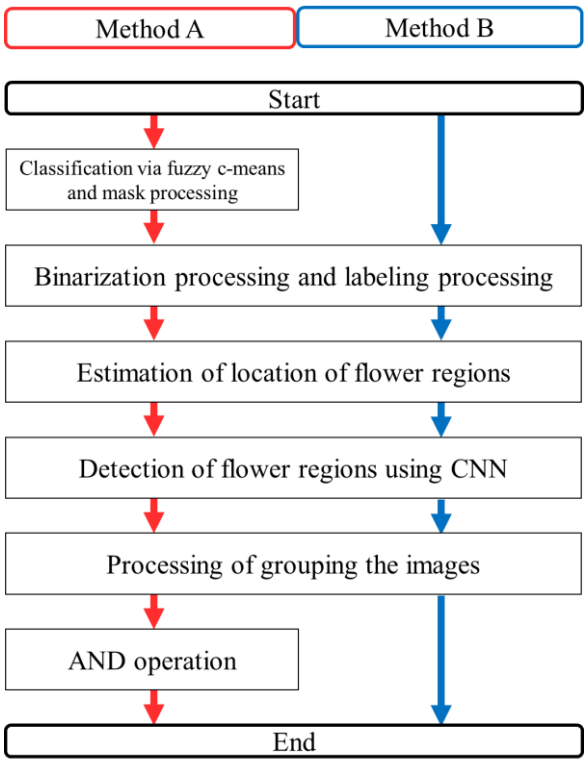


Fig. 4. Flowchart of Analysis Methods.

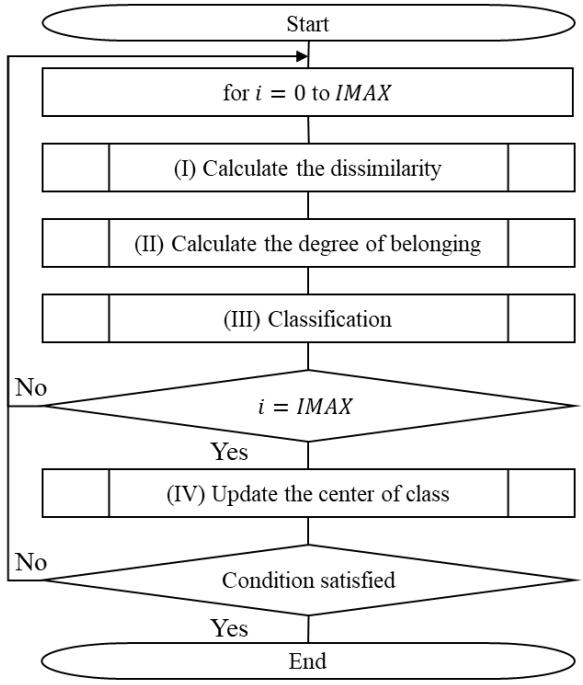


Fig. 5. Flowchart of Fuzzy C-means.

initial value for Class 1 was the average color intensity of the training data used, and the initial value for Class 2 was 0. The termination condition for clustering was set when the number of pixels between classes was < 1% of the total number of pixels. The degree of attribution of Class 1 was divided into 12 levels using the level-slicing method. Finally, the feature image classification results using the merged image were compared with the color chart used for classifying the images to identify the regions classified as flower regions and to obtain an image in which regions other than flower regions were masked.

3.2 Binarization Processing and Labeling Processing

First, two types of binarized images were created from the UAV data and the created mask image: a) binarization focusing on brightness and saturation values and b) binarization using edge detection and discriminant analysis methods. In pre-processing step a), binarization is performed using the threshold value shown in Equation (2).

$$\begin{aligned} 0 \leq S \leq 90 \\ 240 \leq V \leq 255 \end{aligned} \quad (2)$$

Next, a four-neighborhood labeling process was applied to each of the two binarized images.

3.3 Estimation of Location of Flower Regions

For each region obtained from the labeling process, a flower region is estimated if the following conditions are satisfied.

- The aspect ratio of the frame is around 1.0.
- The number of pixels per side of the frame was within the range of 2–40 pixels.
- White pixels in the frame are more than 40%.

3.4 Detection of flower Regions Using CNN

First, the center coordinates of each region obtained from the flower region location estimation process are calculated and extracted from the input data with image sizes of 16 × 16 (pixels) × 3 (bands) and 32 × 32 (pixels) × 3 (bands). Next, the extracted images were applied to Models A and B using a CNN[9], and the regions detected by both models were determined to be flower regions. Finally, the Euclidean distance was calculated for each region of the flower region detection results, and regions within 40 pixels were discriminated as one individual.

3.5 AND Operation

In this study, the flowering regions identified from all the images were denoted as Convallaria keiskei flowering regions. Specifically, the regions extracted from each image using the AND operation were denoted as Convallaria keiskei flowering regions.

3.6 Evaluation Measures

To compare methods A and B and validate method A, the precision and F-measure[10] were used as evaluation indices and calculated using equations (3) and (4), respectively.

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Fmeasure = \frac{TP}{TP + \frac{1}{2}(FP + FN)} \quad (4)$$

4. Results and Discussion

Fig. 6 shows magnified images of the detection process implemented on the images from the estimation results of methods A and B. In Fig. 6, (a) and (b), and (c) and (d) magnified the same location, respectively. Fig. 6 (a) and (b) show that the detection performed by methods A and B reported correctly detecting flower regions. Fig. 6 (d) shows that false positives were produced in the detection performed using method B. In contrast, Fig. 6 (c) shows that method A did not produce false positives. Table 2 summarizes the average values of the precision and F-measure calculated using the methods A and B. Table 3 summarizes the number of data that improved or decreased from the method B in each of the evaluation indices. Compared to the method B, the precision rates were improved in all the UAV data, and the F-measure rates were improved for 6 of the 7 UAV data. Method A excluded areas similar to flower regions by using classification via FCM.

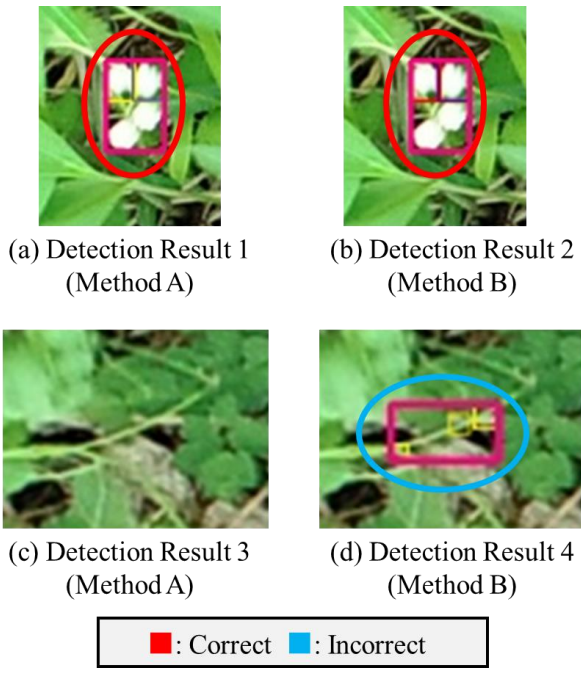


Fig. 6. Magnified images of detection results (image E).

We believe that this process enables method A to detect flower regions with fewer false positives than method B. Even using data acquired in 2022, method A can detect flower areas with higher accuracy than method B. In other words, we believe that Method A is useful for detecting flower regions.

However, as shown in Fig. 7, the methods A and B failed to detect a flower region hidden by a leaf region. The dataset used to train the model did not contain images in which the flower regions were hidden by leaf regions. Therefore, it is considered that the model did not learn the features of partially hidden floral regions well and could not detect flower regions hidden by a leaf region. To improve the accuracy, it is necessary to study the detection method for flower regions hidden by leaf regions.

5. Conclusions

In this study, we evaluated the combined CNN and

Table 2. Average values of the precision and F-measure.

	Precision	F-measure
Method A	0.5021	0.5309
Method B	0.4640	0.5545

Table 3. Number of data that improved or decreased from the method B in each of the evaluation indices.

	Precision	F-measure
Increased	7/7	6/7
Decreased	0/7	1/7



Fig. 7. Example of flower region with detection leakage (image G).

FCM-based detection method (method A) using UAV data obtained in 2022. We compared the detection accuracies of the method A and the CNN-based detection method (method B). The method A determined the Convallaria keiskei flowering regions with a smaller number of false positives than the method B. In this study, the target accuracy was set at 70% or better, based on the opinions of the workers. In the future, further study on improving accuracy will be conducted. In addition, we plan to create orthomosaic images of the target area and study methods to estimate the distribution status of Convallaria keiskei.

Acknowledgment

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