DETECTION METHOD OF CONVALLARIA KEISKEI USING CNN AND FUZZY C-MEANS

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ABSTRACT: Unmanned aerial vehicles (UAVs) are being applied in various disciplines, such as agriculture, surveying, and logistics. Farmland crop growth has been monitored using UAVs. *Convallaria keiskei,* a plant species indigenous to Japan, was on the verge of extinction. *Convallaria keiskei* was protected and managed manually. Applying image processing and machine learning automates *Convallaria. keiskei* classification, helps estimate the increase in efficient colony numbers, and reduces the detection cost. In a previous study, we proposed a flower number estimation method by combining image processing and a convolutional neural network (CNN). However, several regions were misidentified as flowering regions, and the subject numbers were reduced. Therefore, we herein propose a novel detection method that combines image processing, CNN, and fuzzy c-means. The F-measure was used as an evaluation index, which increased in twelve of thirteen images. While the previous method misidentified flowerless regions in an image as flowering regions, the proposed method did not. The proposed method lowered the misidentification as it ignored the regions that appeared similar to flowering regions, exhibiting reduced misidentification of *Convallaria keiskei* flowering regions than the previous method.

1. INTRODUCTION

Unmanned aerial vehicles (UAVs) are being applied in various disciplines, such as agriculture, surveying, and logistics. Farmland crop growth has been monitored using UAVs (Wang et al, 2018; Kumar et al, 2021). *Convallaria keiskei,* a plant species indigenous to Japan, was on the verge of extinction. *Convallaria keiskei* was protected and managed manually. Moreover, stepping on vegetation during manual management resulted in crop loss. Applying image processing and machine learning automates *Convallaria keiskei* classification, helps estimate the increase in efficient colony numbers, contributes to efficiency enhancement, and reduces detection cost.
In a previous study, we proposed flower number estimation by combining image processing and a convolutional neural network (CNN) (Shirai et al, 2020). However, several flowerless regions were misidentified as flowering regions, and the subject numbers were reduced. Therefore, we herein propose a novel detection method that combines image processing, CNN, and fuzzy c-means (FCM) to reduce the image misidentification.

2. STUDY AREA AND MATERIALS

2.1 Study Area

Convallaria keiskei plants bloom between late May and mid-June annually in the Tohoku region and Hokkaido, Japan. A typical *Convallaria keiskei* plant produces approximately 5-10 white flowers and two leaves per colony. In this study, *Convallaria keiskei* colonies in Biratori-cho, Hokkaido were observed. *Convallaria keiskei* was declared as endangered in 1975 in Biratori-cho. Thenceforth, *Convallaria keiskei* has been managed manually and its production was maintained stably (Biratori-cho tourism association web page). As lack of successors is a social problem in Japan, establishing an automatic *Convallaria keiskei* management method is essential.

2.2 UAV Data

Two UAV images sets, a) images A–F (captured on June 7, 2019) and b) images G–M (captured on June 12, 2020) were captured from a height of about 2 m using a camera on the DJI Phantom 4 Pro. Figure 1 depicts the images of a typical flowering region.

2.3 Model Data

Here, CNN-based flower region extraction method was trained using two model types (Section 3.4), model A with 16 × 16 pixel images, 3 bands, and one flower, and model B with 32 × 32 pixel images, 3 bands, and a few flowers (Fig. 2).

3. PROPOSED METHOD

The method included FCM, binarization, location estimation, flower detection, grouping, and an AND operation. Figure 3 depicts the flowchart outlining the proposed and previous methods.

3.1 Classification via Fuzzy c-means and Mask Processing

The remote sensing data (UAV data) contained certain unclear images. Therefore, the FCM clustering method (Takagi et al, 2004) was used, which included the unclear images in the analysis. Figure 4 depicts the FCM flowchart.

(a) Image A (b) Example of the flowering region

Figure 1 Images of a typical flowering region.

(a) Model A (b) Model B

Figure 2 Typical data used in models A and B.

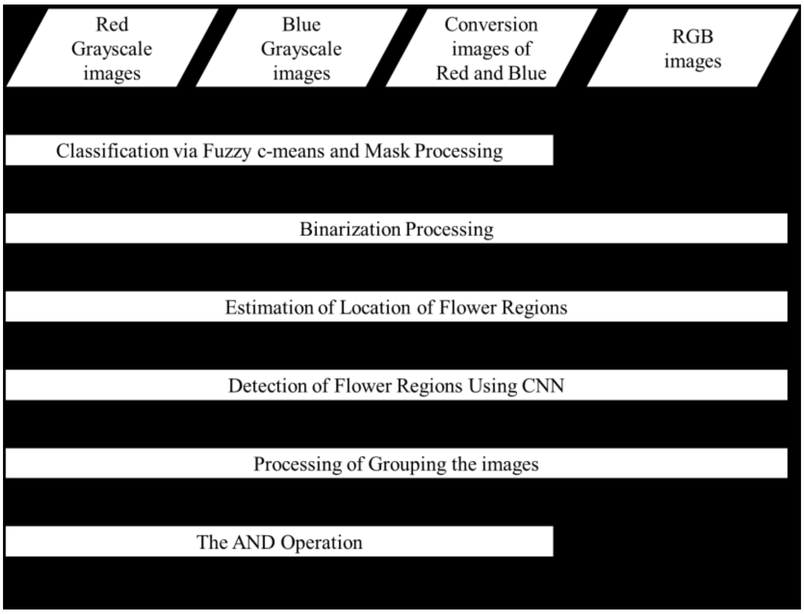

Figure 3 Flowchart outlining the proposed and previous methods.

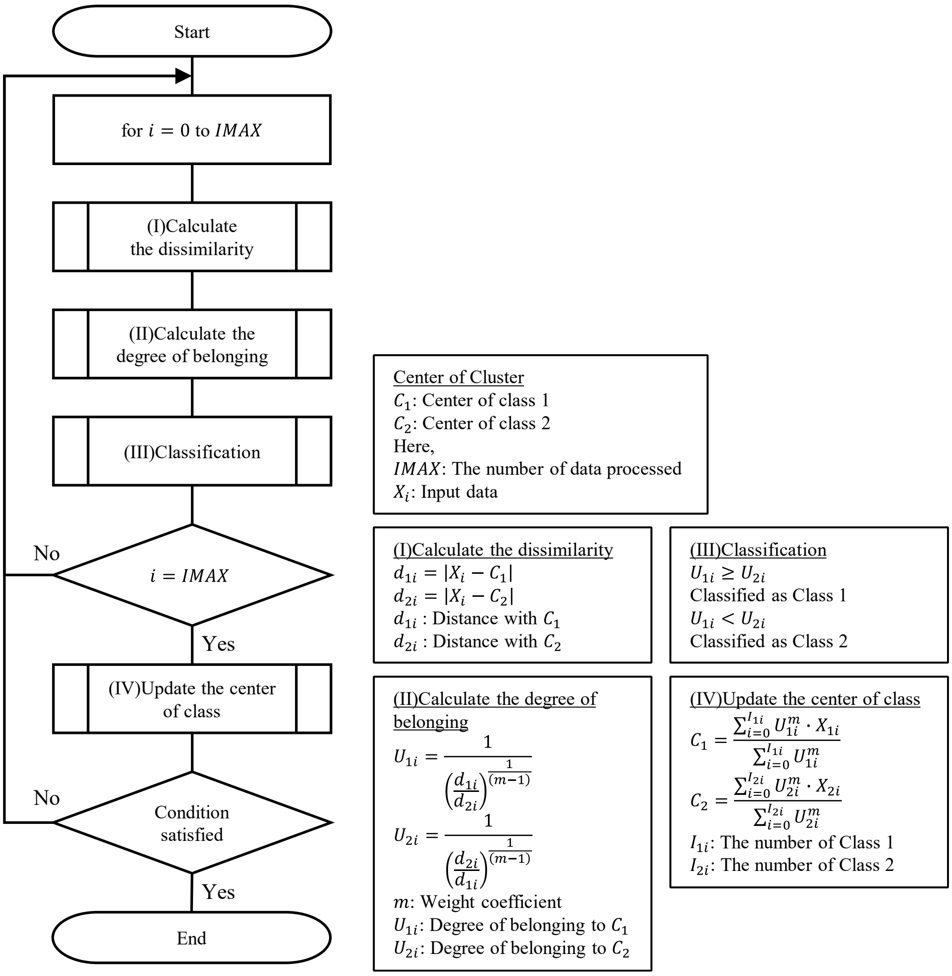

Figure 4 FCM Flowchart.

The images were generated using the UAV data and the merged images were obtained from model A training data. We used the Red and Blue color information to distinguish between the flower and leaf regions, generate Red and Blue grayscale images, and convert Red and Blue images. The images were converted following Eq. (1)

$$DN = Red * 5 + Blue, \tag{1}$$

where DN, *Red,* and *Blue* denote the converted image digital number, and red and blue color intensities in the original images, respectively.
Further, the target area was divided into two classes: class 1 and 2. Initial values of class 1 and 2 were considered using model A's average color intensity and as zero, respectively. The clustering was considered complete when the pixels between the two classes reached ≤ 1% of the total number of pixels. The classification criteria for class 1 included twelve levels. Further, the classes to which the flowering area in the merged image using model A belongs were extracted as the target regions, and the remaining regions were masked. Figure 5 depicts the mask processing flowchart.

3.2 Binarization Processing

Convallaria keiskei flowering regions were brighter and less saturated. Moreover, as the flowers were white, the boundaries of the surrounding leaves and soil were distinct. Therefore, the regions extracted, as discussed in Section 3.1, and the UAV data were binarized using brightness, saturation, and edge data. Additionally, each calculated data point was labeled based on a four-sided neighborhood.

3.3 Estimation of Location of Flower Regions

The frames were obtained upon labeling, established for each region and used to locate the flowers. The flowering regions were identified based on the following conditions:
The frame aspect ratio was approximately 1:1.
The pixel numbers on one frame side was within the range of 2 - 40.
The white pixel percentage in a frame was ≥ 40%.

3.4 Detection of Flower Regions Using CNN

The CNN feedforward network (Harada, 2017) contained convolutional and pooling layers. It enabled learning using the image shapes. Figure 6 depicts the CNN model employed in this study. Models A and B were trained using the input images. Flowering regions were detected using the trained models. Here, the regions detected using both the models were determined to be the flowering regions.

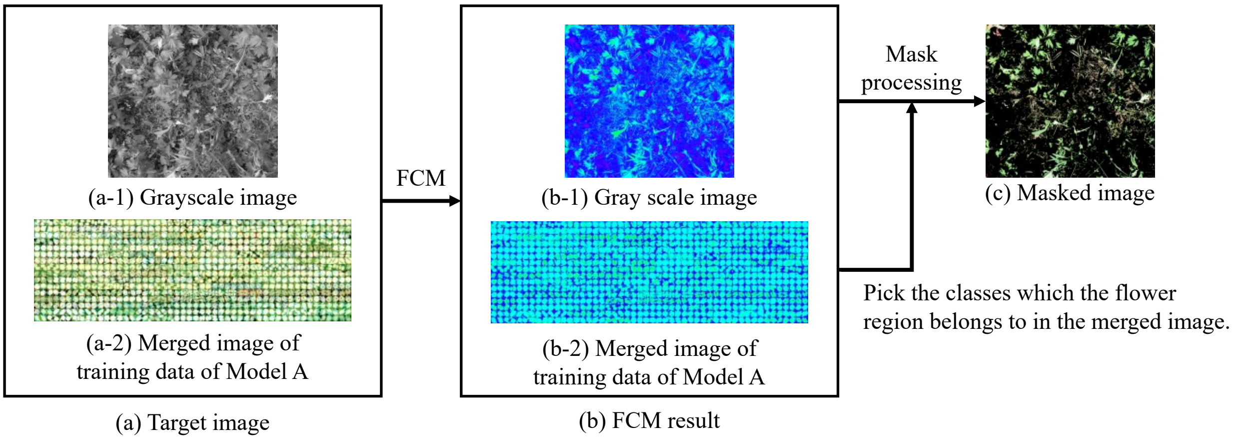

Figure 5 Mask processing flowchart.

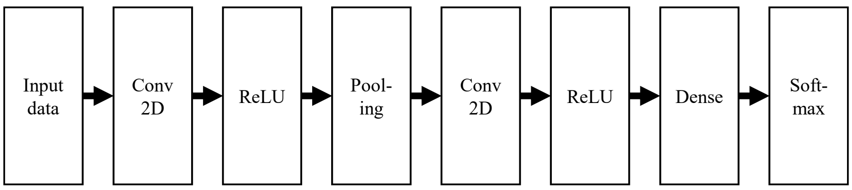

Figure 6 CNN model.

3.5 Processing of Grouping the images

The Euclidean distance was calculated for each flowering region. The regions within 40 pixels were considered as one region.
Therefore, the regions with two or more flowering regions were recognized as one region.

3.6 The 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.

4. RESULTS AND DISCUSSION

4.1 Evaluation Method

We compared the proposed and previous methods' outcome and validated the proposed method. Previous method lacked FCM (Shirai et al, 2020). Here, $Fmeasure$ (Harada, 2017) was used as an evaluation index, which was calculated using Eq. (2).

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

Here, TP, FP, and FN denote correctly, incorrectly detected, and undetected flowering regions, respectively. The $Fmeasure$ ranged from 0.00 to 1.00. Higher $Fmeasure$ value indicated better performance.

4.2 Comparison Between Proposed Method and Previous Method

Figure 7 depicts *Convallaria keiskei* colony detection in image F. Although the previous method misidentified flowerless regions in the image as the flowering regions, the proposed method did not. The proposed method lowered false detection as it ignored the regions that were similar to flowering regions. Table 1 lists the $Fmeasure$ values for each image. The $Fmeasure$ was observed to be increased in twelve of the thirteen images, suggesting that the proposed method exhibited a smaller number of false positives than the previous method in detecting *Convallaria keiskei* flowering regions.

5. CONCLUSIONS

In this study, we proposed a *Convallaria keiskei* flowering region identification method that employed CNN and FCM. We compared the proposed and previous methods' detection accuracy. The following conclusions were drawn.

a) The proposed method determined the *Convallaria keiskei* flowering regions with a smaller number of false positives than the previous method.

b) The red and blue color information, and their merging feature were employed in *Convallaria keiskei* flower detection.

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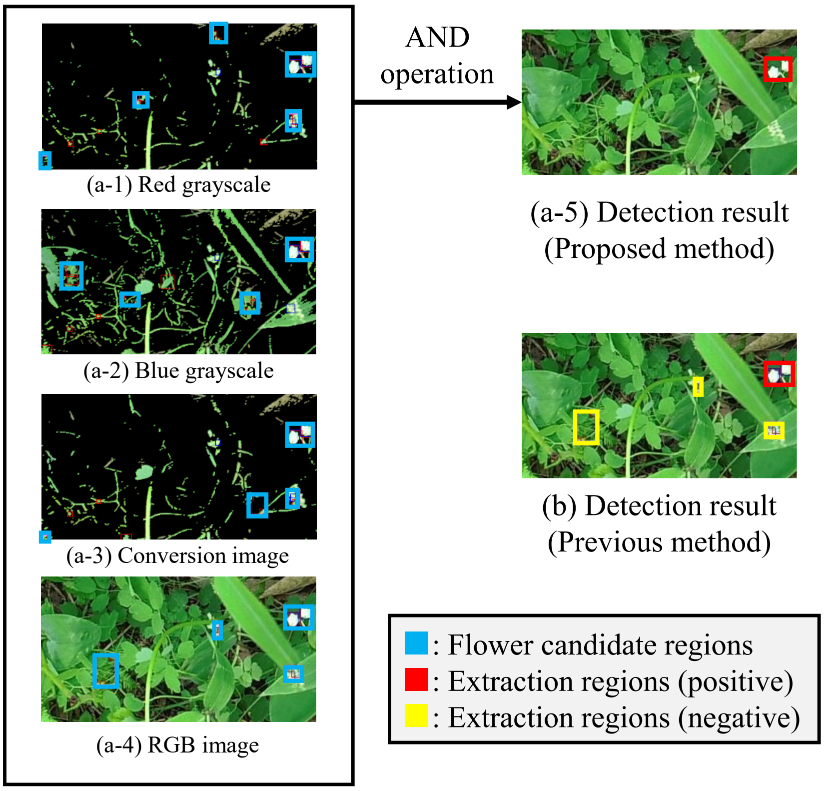

Figure 7 *Convallaria keiskei* colony detection (image F; partially enlarged).

Table 1 $Fmeasure$ obtained using the proposed and previous methods.

Image	Proposed method	Previous method	Difference
A	0.7826	0.6923	0.0903
B	0.2951	0.3056	-0.0105
C	0.7391	0.7347	0.0044
D	0.8246	0.8197	0.0049
E	0.5000	0.4118	0.0882
F	0.5714	0.4889	0.0825
G	0.2069	0.1667	0.0402
H	0.3019	0.2581	0.0438
I	0.7778	0.7579	0.0199
J	0.2581	0.2105	0.0476
K	0.2222	0.1905	0.0317
L	0.3111	0.2414	0.0697
M	0.5455	0.4242	0.1213

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