

## DETECTION AND MAPPING OF HAIRY VETCH IN IMAGES OBTAINED BY UAVS

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### ABSTRACT

Recent advances in unmanned aerial vehicles (UAVs) for civilian use make it possible to regularly monitor fields at spatial and temporal scales that would be difficult to achieve using conventional methods. Mapping the undercover area of a specific plant in images can contribute to compare its annual expansion ability. Hairy vetch is a moderately winter-hardy species. In this study we try to detect hairy vetch in aerial images by using color and texture features. Images obtained from Tone river shore in Gunma prefecture, Japan. Color features extract based on hairy vetch leaves and flowers separately. Grey Level Co-occurrence Matrix (GLCM) used for texture feature extraction. Results show feasibility of using purpose method in discriminates between hairy vetch and different plants in aerial imagery.

### 1. INTRODUCTION

The unique characteristics of aerial images provide by UAVs like high resolution, low cost, fast, reliability and easy to use encouraged studies about plants detection and recognition systems. Another important exclusivity of UAV images refers to distance between reflection surfaces and sensors which distributes to receive more accurate information. Discrimination of the plants in their different stages of development needs images at very high spatial resolution, often in the order of mm or very few cm [1], [2]. The best suitable tools with both characteristics is unmanned Aerial Vehicles; UAVs fly at low altitude (maximum flight altitude in Japan is 150 meters) which are able to provide high resolution images, and also they can be lunched in a very short time which allow to take images in any plants' life stage that is necessary to discrimination.

Hairy vetch, also called sand vetch, is a moderately winter-hardy species. It uses by organic growers as a winter cover crop and in no-till farming, as it is both winter hardy and can fix atmospheric nitrogen. Hairy vetch was introduced to Japan as cover crop in abounded patty fields. Hairy vetch was most promising for the weed control in abandoned fields because of its ability to die off during summer season to make a thick straw-like mulch [3].

Detect and mapping the plants in field can have a various application. Mapping the undercover area of a specific plant in georeferenced images can contribute to

compare its annual expansion ability. Expansion ability determine the ability of a specific plant to be either an invasive variety or not.

In general, textures are complex visual patterns that have characteristics like brightness, color, slope, size, etc. Thus texture can be regarded as a similarity grouping in an image [4]. There is several approach to texture analysis and texture feature extraction like structural, statistical, model-based transform, etc. some of the most popular statistical texture features are derive from GLCM [5]. Haralick introduced 14 textural features derived from GLCMs [6].

In this study we try to illustrate the feasibility of purposed method in discriminating plants species in real field complex aerial images obtained by UAVs. Another end for this study is to detect hairy vetch plant in real field. Detecting the hairy vetch will prepare aerial images to map the under covered area to compare the annual expansion of hairy vetch.

### 2. RELATED WORKS

J.m. Pena et al (2015) tried to detect weeds seedling in sunflower field. The study quantified the efficacy and limitations of remote images collected with a UAV for early detection of weed seedlings. They showed that the ability to discriminate weeds significantly affect by the imagery spectral (type of camera), spatial (flight altitude) and temporal (the date of the study) resolutions. Their results showed the requirements on spectral and spatial resolutions needed to generate a suitable weed map early in the growing season, as well as the best moment for the UAV image acquisition [7].

C. Huang et al (2014) proposed an alternative learning-based approach using feature learning to minimize the manual effort required. They apply this system to the classification of invasive weed species. In this study, they apply feature learning to generate a bank of image filters that allows for the extraction of features that discriminate between the weeds of interest and background objects. These features are pooled to summarize the image statistics and form the input to a texton-based linear classifier that classifies an image patch as weed or background. They evaluated their method to weed classification on three weeds of significance in Australia: water hyacinth, tropical soda apple and serrated tussock. Results showed that collecting images at 5–10 m resulted in the highest classifier accuracy up to 94% [8].

### 3. PROPOSED METHOD

A new method based on color feature and GLCM was proposed. Our methodology can be decomposed in three steps:

1. Data collection
2. Image pre-processing
3. Classification

#### 3.1. Data collection

A quad-copter was used to gather all the imagery in this study. Provided images was passed into a feature extractor as input images to determine local feature vector based on color and GLCM. Also a set of sample images provided and pass into the feature extraction step. Feature vector passed to a classifier to be classify base on similarity with sample images features. Our methodology can be describe in figure (1).

All the imagery was done June 6th, 2016 at Itakura town, Gunma prefecture, Japan. Sky was covered by cloud but Light condition was sufficient and natural. At first, two area were check by agriculture experts to select best data collection sites in real condition. Due to the time limits in imagery, highest proper altitude (10m) selected for data collection. Sites orthomosaic images sample are shown in figure (2).

To implement the color filter boundaries, hairy vetch cultivated in greenhouse. A set of 287 images of hairy vetch leaves in black background obtain by cutting leaves from inside the images. Also a set of hairy vetch flowers images obtain in a same procedure but flowers images cut from input images obtained in real field. This images sets used for calculate the mean and standard deviation of leaves and flowers color in RGB color space.

#### 3.2. Image pre-processing

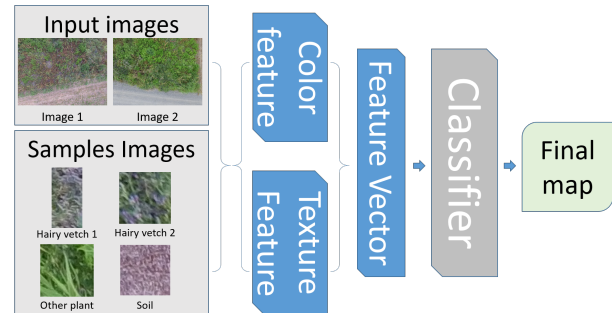
Color is the basic feature, color histograms are commonly used for color feature extraction. To extract color feature two color masks applied on input images. First for leaves and other one for flowers. Color masks boundaries selected as presented in tables 1, 2.

Textural features contain information about the spatial distribution of tonal variation within a band [6]. A co-occurrence matrix C is a matrix that is defined over an image to be the distribution of co-occurring values at a given offset. . This matrix is defined over an  $n \times m$  image I, parameterized by an offset  $(\Delta x, \Delta y)$ , as:

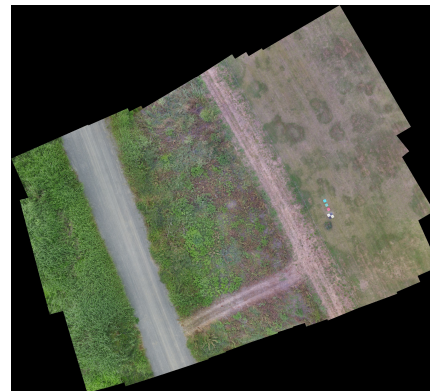
$$C_{\Delta x, \Delta y}(i, j) = \sum_{p=1}^n \sum_{q=1}^m \begin{cases} 1, & \text{if } I(p, q) = i \text{ and } I(p + \Delta x, q + \Delta y) = j \\ 0, & \text{otherwise} \end{cases}$$

Where  $i$  and  $j$  are the image intensity values,  $p$  and  $q$  are the spatial positions in the image I and the offset  $(\Delta x, \Delta y)$  depends on the direction and distance which used. GLCM

used to extract texture features. To calculate the GLCM not only the displacement (distance from pixel of interest) but also the orientation of neighbor pixels must be considered. GLCM extracted in four orientations 0, 45, 90 and 135 degree with three displacements which are 2, 4 and 12 pixels (Figure 3). Contrast, Energy, Correlation, Homogeneity and Entropy of GLCMs extracted as texture features. Meaning of each property in actual analysis case is explained in [6], [9] and [10].



**Figure 1.** Algorithm pipeline: algorithm receives aerial images as input images and the result of classification will show the spatial coordination of hairy vetch in each input image as final map.



**Figure 2.** Study area orthomosaic image

**Table 1.** Maximum and Minimum boundaries for leaves color.

	Red	Green	Blue
Minimum	50	62	38
Maximum	76	92	58

**Table 2.** Maximum and Minimum boundaries for flowers color.

	Red	Green	Blue
Minimum	98	91	111
Maximum	128	119	146

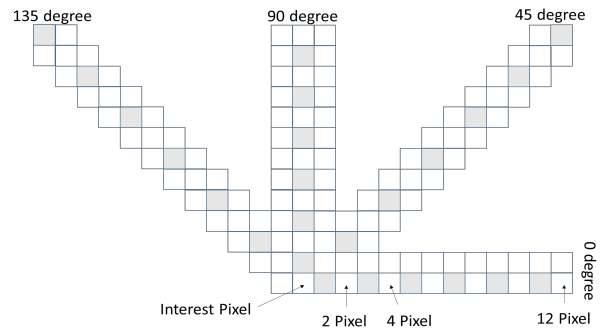
In our method we compute the GLCM properties for sample images (Figure 1); also those properties will compute for a window with same size as sample image so that all the pixels in each input image select as the center of window. Then the calculated properties for each window will store in a matrix as parameters for corresponding interest pixel with same position in input image. This procedure will make the feature vector for each input image.

### 3.3. Classification

In this study we used the simple absolute difference of each parameter in feature vector from the corresponding parameter of sample images as the classifier. A set of boundaries were selected as interest distance for each parameter by experience. Boundaries selected by a supervised procedure. Boundaries are presented in table 3.

**Table 3.** Selected boundaries for each parameter in classifier.

Parameter	Boundary value
Contrast	0.05
Energy	0.003
Correlation	0.001
Homogeneity	0.001
Entropy	0.375



**Figure 3.** distance and angle in GLCM.

## 4. DISCUSSION

This research was intended to explore the feasibility of the described methodology. In the current system, there are several limitations, and correspondingly, several potential improvements can be listed. First, Complexity of images in real field are very high. This complexity cause difficulty in matching images for orthomosaic them. One of the reason for complexity is change in orientation and overlapping of the plant leaves from one image to other.

Second, color is highly light dependent which means color of same species can vary from image to



**Figure 4.** GLCM prosperities of 4 sample images in different angles and displacements.

other. This variation also could happen for different species. Colors of same plant are different in different life stages of plant. Therefore, applying other color space than RGB might help to solve the problem.

Third, the camera lens angle was  $94^\circ$ . It cause high variation in shape and color of plants such that a same plant in center of image are vary from one near the edge of image. This issue address the importance of scale and orientation invariant methods for feature extraction.

In order to compare ability of GLCM in extract effective properties of different textures; four samples selected from all over the study area. These are samples selected randomly and are include two hairy vetch samples, one soil and one sample of other plants. Samples were used to extract the five parameters of GLCM which are Contrast, correlation, energy, homogeneity and entropy. Highest similarity between hairy vetch texture properties observed in contrast and correlation while homogeneity has lowest variation in similarity difference (Figure 4). The GLCM homogeneity of any texture is high if GLCM concentrates along the diagonal, meaning that there are a lot of pixels with the same or very similar grey level value. The larger the changes in grey values, the lower the GLCM homogeneity making higher the GLCM contrast. The range of homogeneity is  $[0,1]$ . The average for homogeneity is 0.66 through all samples. It shows there are a lot of pixels with the same or very similar grey level value. It can explain the miss-classification of soil or other plants as hairy vetch in results (figure 5, 7). By utilize the color filtering result (figure 6), it seems that method's accuracy can be improved. However, it addresses potential of utilizing the other classifier to improve the accuracy.

## 5. CONCLUSION

Results of initial classification show the feasibility of proposed method to detect the hairy vetch in UAV imageries. By comparing the results of color filtering and texture analysis we can realize the potential of proposed method to implement an automatic algorithm to detect and map the hairy vetch (or other plants) in aerial imagery. However, the lack of ground-trust information and unproportioned hairy vetch leaf size to imagery resolution ratio prevent us from calculate the accuracy of method in this stage. In feature works we will try to emphasize on approve the accuracy of algorithm. Experiments show that classification step play a significant role in plant detection. High variation in color shows that in feature work we should pay attention to use more effective color filtering or apply other color spaces to approve the algorithm.

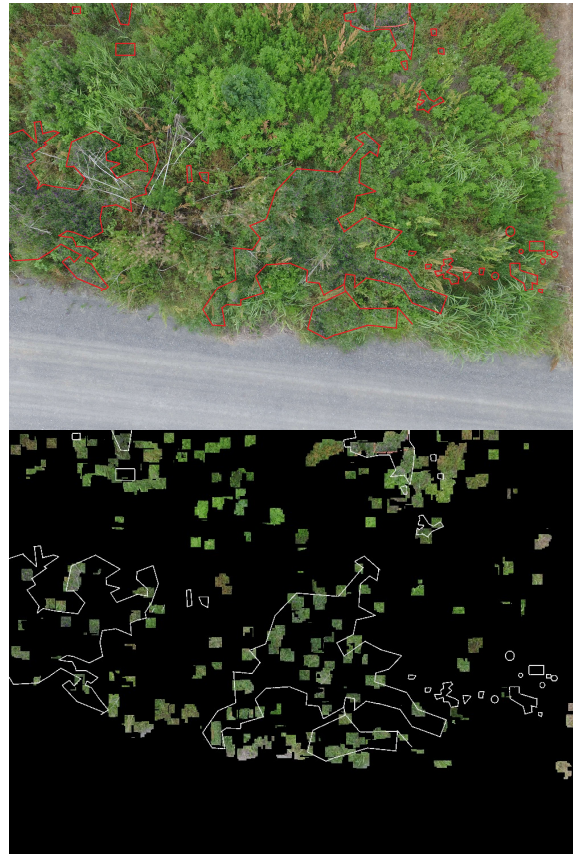
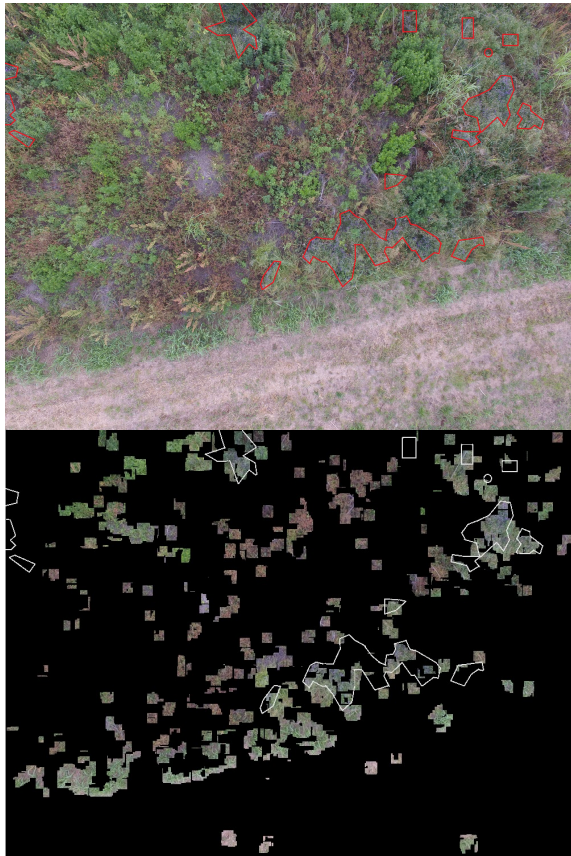


Figure 5. Ground trust tag (up) and Texture analysis result (down) for image 2



Figure 6. Color filter result for image 2



**Figure 7.** Ground truth tag (up) and Texture analysis result (down) for image 1

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